

US EPA ARCHIVE DOCUMENT

U.S. ENVIRONMENTAL PROTECTION AGENCY (EPA)

+ + + + +

FEDERAL INSECTICIDE, FUNGICIDE AND RODENTICIDE
ACT SCIENTIFIC ADVISORY PANEL (FIFRA SAP)

+ + + + +

REEVALUATION OF THE HUMAN HEALTH EFFECTS OF
ATRAZINE: REVIEW OF EXPERIMENTAL ANIMAL AND IN
VITRO STUDIES AND DRINKING WATER MONITORING
FREQUENCY

+ + + + +

DOCKET NO.: EPA-HQ-OPP-2010-0125

+ + + + +

THURSDAY,

APRIL 29, 2010

+ + + + +

The Panel convened at 8:30 a.m. in the
Hamilton Ballroom of the Hamilton Crowne Plaza

Hotel, located at 1001 14th Street, N.W.,
Washington, D.C., Steven G. Heeringa, Ph.D.,
Chair, and Kenneth M. Portier, Ph.D., Session
Chair, presiding.

FIFRA SAP MEMBERS PRESENT:

STEVEN G. HEERINGA, Ph.D., Chair

KENNETH M. PORTIER, Ph.D., Session Chair

JOHN R. BUCHER, Ph.D., DABT

JANICE E. CHAMBERS, Ph.D., DABT, ATS

GERALD A. LeBLANC, Ph.D.

DANIEL SCHLENK, Ph.D.

FQPA SCIENCE REVIEW BOARD MEMBERS PRESENT:

SUSAN F. AKANA, Ph.D.

RICHARD H. COUPE, Ph.D.

KENNETH BARRY DELCLOS, Ph.D.

PENELOPE A. FENNER-CRISP, Ph.D., DABT

ROBERT J. GILLIOM, Ph.D.

RICHARD GREENWOOD, Ph.D.

WILLIAM L. HAYTON, Ph.D.

STEVEN D. HOLLADY, Ph.D.

TERESA H. HORTON, Ph.D.

KANNAN KRISHNAN, Ph.D.

HERBERT K.H. LEE, Ph.D.

KEVIN T. O'BYRNE, Ph.D.

NU-MAY RUBY REED, Ph.D., DABT

JEAN F.L. REGAL, Ph.D.

DANIEL J. SELVAGE, Ph.D.

CARMEN J. WILLIAMS, M.D., Ph.D.

LINDA J. YOUNG, Ph.D.

ALSO PRESENT:

JOSEPH E. BAILEY, Designated Federal Official

Opening of Meeting and Administrative Procedures

Introduction and Identification of Panel Members

Charge to Panel

Charge to Panel - Question 2

Approaches to Evaluating Water Sampling Strategies and Frequency of Monitoring

Question 2.1. 88

Question 2.2. 114

Question 2.3.125

Question 2.4.136

Wrap up and Adjourn 169

1 P-R-O-C-E-E-D-I-N-G-S

2 8:34 a.m.

3 MR. BAILEY: Okay, this is the last
4 day of the FIFRA Scientific Advisory Panel
5 meeting on atrazine reevaluation. I am Joe
6 Bailey, serving as Designated Federal Official.
7 Dr. Portier is the chair and I will turn the mike
8 to him.

9 SESSION CHAIR PORTIER: Good morning.
10 Thank all of you for sticking with us into this
11 fourth day of discussion. Hopefully not a full
12 day of discussion, but it remains to be seen.

13 Just to give the panel and the
14 audience a little kind of idea of what our plans
15 are this morning, I am going to revisit Question
16 1.9, just to get any concluding remarks and kind
17 of make sure that at least the panel is clear
18 that all of our ideas have been captured.

19 We will then go to some presentations
20 from Syngenta and EPA on clarifying comments
21 related to the hydrology and the simulations that
22 they did. The panel members assigned to those

1 questions have been working very hard the last
2 three days to really understand what both
3 Syngenta and EPA has done so that they can make
4 sure that their remarks are to the point.

5 And while it has been nice for them to
6 have these discussions on the side, those
7 discussions need to come back into the full room
8 so they are captured into the public record.
9 That is the gist of a public meeting.

10 So we will have those presentations
11 hopefully no more than a half hour with questions
12 and then we will begin with the four hydrology
13 questions. And at that point, hopefully we will
14 be able to close the public meeting and begin to
15 write our report.

16 So with that, I am going to, I don't
17 know where we are on the slides, but we are going
18 to go back to Question 1.9 which if you remember,
19 these are the questions that relate to the risk
20 assessment and the PK and primarily deal with
21 issues of frequency and duration of water
22 monitoring as it relates to toxicological

1 concerns. And I have asked Dr. Reed and Dr.
2 Krishnan, I warned them that I was going to call
3 on them first to start the discussion and then we
4 will open it back up to the panel.

5 Primarily, we don't really want to
6 rehash everything we talked about yesterday but
7 we want to capture any additional thoughts you
8 may have had over the evening. It was an
9 intensive two hours yesterday afternoon and I had
10 to go back and think about a lot of it myself.

11 So with that, Dr. Reed?

12 DR. REED: Yes, the Chair gave me the
13 warning but it was five minutes ago.

14 (Laughter.)

15 SESSION CHAIR PORTIER: You don't get
16 much more for tornadoes, either.

17 DR. REED: Yes, for 1.9, the first
18 part of it, we talked about let me see. I was
19 given 30 seconds.

20 We talked about focusing on downstream
21 events to define the endpoints for risk
22 assessment. So these endpoints have to do with

1 something that is adverse in terms of function or
2 anything that you would define.

3 And we talked a little bit about
4 within the mode of action that we have been
5 talking about in the last three days but also any
6 possible other mode of actions. I have asked if
7 anyone who has a sense of sensitivity difference
8 between animals and humans of the particular
9 endpoint that you are interested in having used
10 risk assessment.

11 But most of the comments are really
12 just to go back and look at the entire database
13 and benchmark those analysis to form endpoints to
14 compare the sensitivity of these endpoints and to
15 include all the steps in the key events and
16 mindful about the acute and short and long-terms
17 duration of exposure and mindful about the
18 toxicity of the metabolites and so some form of
19 toxicity equivalence factor could be applied to
20 it to address all the speciation of the
21 chemicals.

22 And our sort of comments or inclusion

1 for this issue would be also regarding the lack
2 of data from all the previous discussions.

3 And Dr. Horton had graciously offered
4 to come up with maybe more detail. When we talk
5 about key events and I felt yesterday we were a
6 little bit ambiguous about what are the key
7 events, how many, four, eight, or additional mode
8 of action. And so Dr. Horton graciously offered
9 to come up with a new house and maybe more
10 elaborate.

11 So this will be where we want to hear
12 from her. Dr. Horton.

13 DR. HORTON: Now I know why I didn't
14 go into architecture.

15 Okay, I am still working on this new
16 figure but I can give you an idea of what it will
17 look like for the minutes. And it will be a
18 multi-part figure reflecting the charge to the
19 panel to evaluate the MOA and aid the agency in
20 its preparation for the September 2010 meeting.

21 And the goal of agency by 2010 is to
22 develop a draft weight of evidence document that

1 includes points of departures for evaluating risk
2 in infants and children, with the goal of
3 determining the extent to which the current data
4 indicates a need for the Agency to develop a new
5 human health assessment for atrazine and to
6 reconsider, as appropriate, the frequency of
7 drinking water sampling.

8 So to that end, the figure will be a
9 multi-part figure encapsulating the mode of
10 action or the modified mode of action as
11 discussed here, which will be a newly
12 conceptualized mode of action, taking into
13 consideration the data discussed in the last few
14 days. The weight of evidence supporting the
15 various level data that has been discussed using
16 arrows of different weights to indicate the
17 confidence in the various pieces of evidence that
18 have been discussed.

19 And the diagram will recognize that
20 organisms, especially humans, are complex systems
21 and that the systems we have discussing often
22 interact and function as feedback systems with

1 some degree with hierarchical organization and
2 that within that context, atrazine may act at
3 several different levels of the hierarchy. And
4 the key events may occur at any point within that
5 hierarchy. And because these are feedback
6 systems, they may ramify at different levels.

7 The diagram will also attempt to
8 identify where new areas of research may be
9 helpful or where areas of research need to be
10 strengthened. Thank you.

11 DR. MENDEZ: Could I just one second
12 please?

13 SESSION CHAIR PORTIER: Yes, sure.

14 DR. MENDEZ: I just want to clarify
15 for the panel that our intent for September, it
16 is to reevaluate the toxicity not just for
17 infants and children but for the entire
18 population.

19 SESSION CHAIR PORTIER: Sorry, this is
20 Ken Portier. Is this on? Yes, I guess so.

21 In talking with Dr. Horton about the
22 diagram, the one thing that caught me is she took

1 figure three and she said but the way I see it is
2 this way and with CNS at the top and functional
3 at the bottom. And I think that is one of the
4 major changes.

5 It sounds simple but when she talked
6 about top down or something at the top, you know,
7 I was looking at it as atrazine from this chart
8 and she was looking at it as CNS, looking at it
9 in the transposed way. And to me, that clarified
10 a lot of the conversations she had been making
11 all along because she sees it in this rotated
12 version with the central nervous system at the
13 top and functional capabilities at the bottom and
14 atrazine comes in from the side.

15 Dr. Horton and then Dr. Crisp.

16 DR. HORTON: You have to understand
17 that within the world of reproductive
18 endocrinologists and neuroendocrinologists, we
19 divide the world into those of us who work above
20 the belt and below the belt.

21 (Laughter.)

22 SESSION CHAIR PORTIER: Dr. Fenner-

1 Crisp?

2 DR. FENNER-CRISP: I don't know how to
3 top that one.

4 I might suggest that you go back and
5 look in the draft document with respect to the
6 mammary tumor MOA and the figure in there does in
7 fact start with the brain and trickle down.

8 SESSION CHAIR PORTIER: Dr. Cooper?

9 DR. COOPER: I would like to, if I
10 could, also make a comment. I think that figure
11 that you saw there was before it got to
12 Washington.

13 But I am really pleased to hear you
14 make the suggestions that you made because it is
15 an extraordinarily complex set of issues that we
16 are dealing with and the key point, you have
17 captured it, especially when you think of
18 toxicity pathways that was touched on yesterday,
19 they are not linear. That they are probably
20 masses with multiple, perhaps multiple target
21 sites. And to capture that is an extraordinarily
22 difficult thing, especially in a mixed audience

1 like this.

2 The other thing is that the arrows are
3 key to this also. And there is a considerable
4 amount of difference in the weight of evidence.
5 But the only thing is, is that we are preparing,
6 you are going to make suggestions about the way
7 the arrows, the thickness of them is that in this
8 case, I think there you can bring in some of the
9 in vitro data that is existing.

10 SESSION CHAIR PORTIER: Dr. Bucher?

11 DR. BUCHER: Yes, I just wanted to
12 bring up the fact I have been involved in a
13 number of discussions over the years on MOA and
14 the development of frameworks for the utilization
15 of MOA with respect to evaluating human cancer
16 information. And one of the things that I think
17 is most important is that the MOAs have to be
18 pretty well developed on, I think the words we
19 have used are compelling, scientifically
20 compelling.

21 And what I am a little worried about
22 here is that we have a very, very complicated

1 potential figure for an MOA that is being
2 introduced at the very end of the meeting and I
3 wouldn't want it to come out of this meeting as
4 something to the world that has been fully
5 evaluated and agreed upon by this group.

6 So I think that whatever you put
7 together should be cast in the right terms that
8 it is a very, you know, it is a suggestion of a
9 way that the agency might want to look at
10 organizing the information rather than being cast
11 as an MOA.

12 SESSION CHAIR PORTIER: Yes, we have
13 talked about that as well. Dr. Krishnan, do you
14 want to talk about PK issues?

15 DR. KRISHNAN: The second part of this
16 question related to the temporal consideration
17 based on toxicity versus monitoring frequency.
18 As much as I would like to talk about PK, I am
19 going to have to be a little bit more implicit of
20 both PK and PD. That is what I am going to try
21 to do and invite Dr. O'Bryne to complete or
22 correct me as I make my comments.

1 In thinking about this, you know,
2 frequency of monitoring versus the temporal
3 profile or temporal considerations of toxicity,
4 we do it in terms of the time course of the
5 atrazine and metabolite in the body, which is
6 essentially the PK consideration, and then the
7 time course or the precursor, the key events or
8 the precursors measured, which could be altered
9 LH cortical levels.

10 First, in terms of the consideration
11 of the time course of atrazine and metabolites or
12 the internal dose. As we talked about yesterday,
13 the uptake or consumption pattern associated with
14 the drinking water combined with the
15 pharmacokinetic considerations, my colleagues
16 mentioned some of the key aspects, particularly
17 the slow absorption rate for example from the
18 drinking water or from oral administrations, the
19 relative short half-life of the parent chemical
20 combined with an extended half-life of some of
21 the metabolites, these things suggest together
22 that in the integrated measure, the internal

1 exposure would be relevant.

2 For example, the chloroforms, the
3 chlorinated form, atrazine plus metabolites that
4 still have the Cl in them. Or there could be an
5 average calculated based on the AUCs over a
6 particular period.

7 So the area under the curves would
8 integrate both the dose and the temporal
9 considerations together, essentially. And I have
10 not seen anything that suggests that the
11 particular Cmax of a parent chemical or
12 metabolite during a specific period is somehow
13 clearly associated with the profile of the
14 precursors measured or the outcome in tox
15 studies.

16 So given those observations, I still
17 tend to think that the overall profile or
18 consideration of pharmacokinetics does not call
19 for very narrow time-based analysis of
20 monitoring. So that is one part of it.

21 The second part is that then you think
22 about the time course of the key events are

1 essentially the precursor or the measurements
2 that are made between the internal dose and the
3 toxicological outcome. In this case, the time
4 course of the LH or the cortical levels.

5 The current complication, in my mind
6 at least, arises from the consideration of the
7 more recent data on the short-term changes in the
8 rats summarized in Table 3 on the HPA/HPG axis,
9 essentially in the four-day experiment. I think
10 that is where some of the discussions yesterday
11 focused on.

12 It is kind of unclear to me if the
13 four-day exposures result in an impact on the
14 precursors, for example, LH or cortical levels.
15 And since they seem to bounce back within the
16 next few days that follow, these four-day
17 experiments which lead to all the discussions of
18 a four-day monitoring frequency, for example, is
19 kind of related to an adapting response, rather
20 than an adverse response. That is a question I
21 ask myself. You know, if it is a four-day dosing
22 that causes an impact on LH and then in four days

1 it bounces back, then the cycle, I guess, it gets
2 back afterwards and so forth, it appears to me
3 more of an adapted response, rather than adverse
4 reproductive outcome per se.

5 Further, depending on the critical
6 effect, I mean, that is one of the reasons why we
7 revisited the MOA figure. Depending upon the
8 critical effect that is going to drive the acute
9 versus chronic assessment, I hesitate to see this
10 single MOA funnel in accommodating all of these
11 outcomes. Specifically, I don't think one MOA
12 will fit all effects acute and chronic. That is
13 where some of my concerns come.

14 So the precursor effects appear to
15 make at least convincing sense to me based on
16 chronic exposures and sustained effects on the LH
17 associated with the reproductive outcome and so
18 on which are not questioned at all.

19 But in terms of the acute exposure and
20 I am still a bit reluctant to suggest anything
21 other than an integrated or an average one,
22 rather than focusing on a four-day period based

1 on these points.

2 Additionally, as I was thinking about
3 this four-day discussion yesterday and some of it
4 came through during the supper time, is that you
5 know, once you take a benchmark, some level of a
6 NOAEL in a rat study, based on the effects on the
7 precursors and then use that as a basis for
8 deriving oral concentrations appropriate for
9 humans, what is the point of relating then back
10 to the four-day frequency there or the duration
11 of the effect in the rat unless we want to
12 protect the rat? Because that is where some of
13 our confusions came from.

14 The focus should be on the dose
15 because we took the dose based on the rat studies
16 and we said well we will use that as a basis to
17 protect the humans. And then you do the
18 calculations and then I don't see the obvious
19 connection of going back with these numbers, back
20 to the four-day frequency. That obvious link, I
21 mean, that is not an obvious link to me, unless
22 you want to calculate the physiological equal and

1 times and so forth. Even there I am not sure you
2 would say it is a worthy effort.

3 As Bob Dedrick, I think, in the '70s
4 derived some of these physiological time
5 equivalents and so forth, those sophisticated
6 calculations could be done but I don't see that
7 being a productive route.

8 So, I don't know if I confused or
9 clarified more but this is what is in my mind,
10 based on discussions we have had.

11 SESSION CHAIR PORTIER: Dr. Greenwood,
12 you wanted to add something to this?

13 DR. GREENWOOD: Yes. I think we were
14 trying to get our heads around this at the end of
15 the session yesterday afternoon. And I think
16 what we saw was that it makes a lot of sense,
17 because you have got to base your protective
18 levels on the hazard. And we saw that there was
19 a lot of sense in basing it on the rodent assay,
20 which is clear, with a clear endpoint and so on,
21 and well supported with evidence.

22 But we couldn't see then why the time

1 should be based on the rodent at all. I mean,
2 this is what Dr. Krishnan just said. We just
3 could not see why you would use a time based for
4 a rat effect. Okay, the dose is important. That
5 is what you use it for, to get the hazard. But I
6 don't think it was ever intended to try and set
7 an exposure time. As Dr. Krishnan said, you are
8 not trying to, a lot of people spend money trying
9 to kill rats and not trying to protect them.

10 So I think we felt that if there were
11 to be an exposure time figured in to the water
12 monitoring, it has really got to be something
13 more human-based. But what that would be is
14 difficult because, as Dr. Horton said, it could
15 be just an hour, the critical period for some
16 endpoints and you are never going to capture
17 that.

18 So we felt that if you go for the most
19 vulnerable stage, maybe during development, it
20 could just be an hour but I would prefer to let
21 Dr. Horton speak to that, I think.

22 SESSION CHAIR PORTIER: Dr. Horton?

1 DR. HORTON: Yes, this is one of the
2 things we will try to encapsulate in the new
3 diagram is the difference between developmental
4 programming effects, which may have long-term
5 outcomes which may not, while exposure may occur
6 during fetal development and may result from
7 short duration exposure but the actual effects
8 may not appear until later in life versus what
9 Dr. Krishnan referred to as an adaptive response
10 occurring in response to an acute exposure. So
11 we will try to capture those two different things
12 because in a physiological sense, the mechanisms
13 of action may be very different.

14 SESSION CHAIR PORTIER: Dr. Bucher?

15 DR. BUCHER: So I understand and I
16 agree with the comments you made about the time
17 issues. But I think that you said something
18 about the fact that if there was a four-day
19 exposure and there was an effect but it was
20 reversible, it wasn't considered an adverse
21 effect. And I would absolutely disagree with
22 that.

1 And if you are talking about an
2 adaptive behavior as simply something that can be
3 reversible, I would disagree with that as well.
4 I think that is not the correct interpretation of
5 toxicology.

6 SESSION CHAIR PORTIER: Dr. Cooper?

7 DR. COOPER: This is not an atrazine
8 paper but in 1993 we published a paper with the
9 acaricide chlordimeform where we showed that a
10 single dose administered on the critical period
11 on the afternoon of proestrus and the clearance
12 of this stuff is pretty quick, blocked the LH
13 surge and delayed ovulation. And everyone said
14 well that is a reversible effect and if you block
15 ovulation, they ovulate the next day, especially
16 a rat. And rats are rats and humans are humans.

17 Well, it turns out that we went on to
18 examine that further. And when you delay
19 ovulation, the ova ages. And as the ova ages, it
20 becomes, I don't know what the right word is, the
21 viability is such that you end up with things
22 like polyspermia and you end up with polyploidy.

1 I think that was Dr. Stoker's master's thesis.

2 And so when you went on and looked at
3 the mothers of those one-time dosed animals which
4 was reversible, if they became pregnant, then
5 that effect was not reversible. There was
6 delayed development, embryo anomalies, reduced
7 litter size. So sometimes a single dose, even
8 though it may apparently be reversible, may not
9 necessarily be that.

10 SESSION CHAIR PORTIER: Dr. Krishnan?

11 DR. KRISHNAN: I think I was cautious
12 in the way I phrased it, but what I had raised as
13 a question or concern was that those effects
14 during the four days on the precursors if you
15 will, the cortical and the LH, if they are
16 clearly associated with the reproductive outcome
17 or the delayed maturation on some of the other
18 whole animal affects, clearly, then I don't ask
19 question aloud. So it is obvious.

20 My understanding or at least the
21 reason why I raised the question was if it was
22 affecting a cycle on then which bounces back and

1 then captures, there is no demonstration of
2 reproductive outcome or other whole animal
3 effects in these studies, which doesn't seem to
4 be the case. If not, please correct me. Then I
5 will take back and I say well three or four-day
6 or even less or more frequent monitoring would be
7 required.

8 So I just want to be clear that I have
9 not misread or misinterpreted.

10 SESSION CHAIR PORTIER: Dr. Reed?

11 DR. REED: Just so that you are having
12 fun here, when I was beginning to do risk
13 assessment and our kids were very young and they
14 asked me what do you do and so I said we just do
15 experiments on rats and mice and bunnies and then
16 we bring that down by hundred-fold. And they got
17 the idea that all the field mice and field rats
18 and bunnies are all very safe.

19 And about the reversibility, I totally
20 agree with Dr. Bucher that reversible effects are
21 still adverse if it is adverse to begin with.

22 Also, a lot of times maternal effects

1 may be reversible. Alkaloids is an example that
2 the fetus is not, when it gets to the fetus
3 effect, fetal effects.

4 But I think, my understanding of this
5 issue about reversibility is that you have a
6 cascade of events and going through the networks
7 or the pathway of the mode of action, there may
8 be a step that you would have effect that there
9 is some sort of threshold so that it will not
10 trigger the next step, then that might be
11 something to consider as "reversible" in that
12 context.

13 But my main comments is that we talk
14 a little bit about area under the curve and blood
15 concentration and so forth. But I think it is
16 important, at least when I am doing PAPK model,
17 the hardest thing is to decide on the dose
18 metrics for rats to human equivalents. And I
19 think that when we get to PAPK or use PAPK as a
20 tool, that we should clear about what is the most
21 appropriate target sites. And I would not
22 preclude the possibility of using peak

1 concentration and just across the board to say
2 area under the curve is the most appropriate. In
3 terms of target site, it might not be serum but
4 could be more pertinent. Could be brain.

5 And so these are the kind of things
6 that I think we need to consider. I don't think
7 it is necessary for us to set in stone to say
8 area under the curve or what target site, or just
9 serum concentration.

10 SESSION CHAIR PORTIER: Dr. O'Byrne?

11 DR. O'BYRNE: I am just listening to
12 these conversations, I am trying to remind myself
13 why I am here. And it was my thought that we had
14 this new data of this 15-minute activation of the
15 HP axis, which was making us reconsider the
16 sampling frequency.

17 Now, my considered opinion is that
18 this 15-minute HP activation is a red herring and
19 it reminds me of Tony Blair's 45-minute weapons
20 of mass destruction argument. And I think we
21 have got to be very careful here.

22 The data, I mean, we have heard these

1 arguments about development and how sensitive
2 they may be but I haven't actually seen any data.
3 We are dealing here with a surge as this sort of
4 benchmark which cannot be separated from cycles.
5 If you don't have surges, you don't have cycles.
6 And the rat has got a four-day cycle and humans
7 have got a 28-day cycle. And the data that we
8 have got in front of us is that the LOEL for
9 atrazine is 3.6 milligrams over 28 weeks or 6.2
10 over four days. And that is what we have to work
11 with. So, I think these are the critical
12 factors.

13 And the discussions about how to
14 extrapolate from the rat model to humans is also
15 quite important, I think, to appreciate. And to
16 fit the physiology into the toxicology is hugely
17 difficult and we struggle with that. And I don't
18 know whether you can extrapolate from some
19 analogies and experimental data.

20 There is one that comes to my mind.
21 If you take a rat and you give it a large enough
22 dose of estrogen, then you will have an LH surge

1 every day at 5:00 or whatever until the thing
2 becomes exhausted.

3 If you give a large dose of estrogen
4 to a woman at any stage during the follicular
5 phase, you stop that cycle dead in its tracks and
6 you will wait 14 days for the next spontaneous LH
7 surge. So I don't know whether you can use that
8 temporal concordance or not but it is hellishly
9 difficult.

10 I don't know if that is of any value
11 at all.

12 SESSION CHAIR PORTIER: I am sure the
13 Agency is going to have to deal with that as they
14 kind of move forward and put this all together.

15 I am going to kind of end it at this
16 point. I just wanted to make a last comment that
17 as I was thinking through this and trying to make
18 the transition to the monitoring and sampling,
19 while it is nice to understand the mechanism of
20 action and understand this stuff, when you really
21 think from a population public health level, you
22 know, you start thinking about a hundred million

1 women, at any one point, any one day, any one
2 point in time, some of them are at the critical
3 level. So the statistic you are probably looking
4 for for monitoring is going to be some kind of
5 daily average that we are not going to exceed
6 because there is somebody at risk every day.

7 So it is nice to know the duration of
8 the impact of a concentration on an individual
9 but when you integrate it over the population, it
10 is going to be an average value that you are
11 looking at. The question is translating that
12 average to a physiologically critical dose that
13 is safe. Right? And that is the concern.

14 So I hope, Dr. Krishnan and Dr. Reed
15 are going to be able to capture this. The reason
16 for doing this is I know this is a critical
17 question and I really want to make sure as we
18 write this up we kind of capture all of this.

19 Thank you. I think, Dr. Cooper, you
20 are done. We are going to bring up the hydrology
21 point.

22 At this point, I think Syngenta is

1 first up. Dr. Hendley, I think has the
2 microphone, followed by Dr. Sielken, followed by
3 Mr. Thurman or Mary Frankenberry. And they
4 promised me to kind of collectively keep this
5 within 30 or 40 minutes. And we will probably,
6 at the end of this presentation, we will probably
7 take our morning break, get our coffee and then
8 go into these questions.

9 A number of pages have been handed out
10 to the panel and they are already being processed
11 to put on the docket, some of which are going to
12 be presented here and some of which have not. A
13 lot of it is clarifying material.

14 We went through the presentation on
15 Monday afternoon kind of quick and that was, I
16 think, the one reason we really want to revisit
17 and make sure we understand what was presented.
18 I know it is early in the morning but I am sure
19 the toxicology physiologists over here are going
20 to kind of sit back and relax.

21 Dr. Hendley.

22 DR. HENDLEY: Okay, this is Paul

1 Hendley from Syngenta again. And we would like
2 to thank you, Mr. Chairman and the panel for
3 giving us an opportunity to clarify some of the
4 handouts that were given.

5 And I think in fairness to the
6 hydrologists, for the rest of you around the
7 panel, you need to realize that between ourselves
8 and EPA, we have talked about five approaches,
9 each of which have examined data in subtly
10 different ways than the hydrologists have
11 properly asked us to clarify exactly how the data
12 were processed so they can better understand the
13 interpretations that have been made.

14 So what I am going to be doing is
15 referring or what we are going to be doing, and
16 incidentally, I have Dr. Sielken on my left and
17 Dr. Chen, the Dr. Chen from Chen et al., which
18 you have seen a number of times, on my right.

19 What we are going to do is talk about
20 the slide number from my presentation and then,
21 if I may, Mr. Chairman, I suggest after these are
22 largely one pages, if we briefly go through the

1 one-pager and then ask to make sure we have
2 addressed the questions, it is more efficient
3 than trying to remember what we said. Thank you
4 very much, indeed, then.

5 Okay, the first one refers to --

6 SESSION CHAIR PORTIER: Can you make
7 that full screen?

8 DR. HENDLEY: I can. I can make it
9 bigger but I am afraid it is in Word. Where is
10 the zoom on this version of Word? It is not the
11 one where -- zoom. Thank you. Is that any
12 better? No, not really. Thank you.

13 It is amazing how Windows changes.
14 You totally forget the version as you move on.

15 Okay, the first one refers to slide
16 ten in the Syngenta presentation, which was about
17 high centiles. There is a very detailed report
18 on the docket, which is Whitmore and Mosquin.

19 The points that I think I would like
20 to clarify that I understand were questions in
21 the minds of the hydrologists were this is
22 finished water. And what we are talking about

1 here is an analysis that follows almost exactly
2 the process in the main report, which was done on
3 the full data set of both SDWA 50,000 data points
4 and VMP/AMP, the 48,000 data points. But this
5 time, they looked at the subsets of data based on
6 the water sources, static, flowing, and mixed.

7 And in addition, they looked at the
8 subset of data based across all community water
9 systems but recorded samples between April 1 and
10 July 31.

11 And so briefly, in that process, each
12 subset of the VMP/AMP data set was taken. The
13 data points were weighted, as described in detail
14 in the report. And we probably don't need to go
15 into that today.

16 The key question I think that was in
17 the mind of the panel was were these data points
18 interpolated. And the answer is they were not
19 interpolated. The centile estimates that were
20 given on slide ten were computed directly from
21 the population of measurements. And then the
22 confidence intervals were obtained as described

1 in the full report and that led to the table in
2 the handout that accompanied the slides.

3 DR. YOUNG: Linda Young. Okay, Paul,
4 I can't figure out, are you talking about this
5 handout, and this slide ten? I can't find slide
6 ten.

7 DR. HENDLEY: Okay.

8 DR. YOUNG: So, I am quite lost.

9 DR. HENDLEY: Okay. I do not have the
10 slide set up here. It is the slide set that I
11 presented. I think it is near the back of that
12 slide, that package of slides.

13 DR. YOUNG: Okay.

14 DR. HENDLEY: There you go.

15 DR. YOUNG: All right.

16 DR. HENDLEY: No, the slide set that
17 starts with potential atrazine exposure in
18 drinking water. You got it. That is slide ten.

19 So that was on the high centiles and
20 it had the data on the full data set, as well as
21 the subsets by source type, static water, the
22 flowing water. And so that was done with no

1 interpolation from the entire set of data points.

2 Any further questions on that one? Okay.

3 The second one refers to slide 12 in
4 that presentation, which you should find says
5 sampling frequency and then 90-day exposure.
6 Okay? Right.

7 So, this is a handout that is
8 describing in more detail the process of
9 developing the data. And the key points here, it
10 was raw water and there were 441 community water
11 system years from -- and now we can read it --
12 from 137 community water systems.

13 This was from the atrazine monitoring
14 program. So they were seven-day intervals during
15 the growing season and every two weeks during the
16 rest of the season. And for each one of those
17 441 community water system years, linear
18 interpolation was used in this case to create a
19 365 daily concentration profile. From that
20 interpolated profile, 90-day rolling averages
21 were computed and the maximum one was selected
22 for each community water system year. That was

1 the true value against what we are going to
2 compare our samples.

3 There were a number of sampling
4 designs tested and just to be clear, they are as
5 shown on the table on the other side. Overleaf,
6 as the Brits would say. This is the atrazine
7 monitoring protocol, right to extreme right of
8 that table. And in January, there was one every
9 two weeks, which works out to approximately three
10 sets of samples in January, two in February, two
11 in March, and this just happens to be because of
12 calendar weeks and then you go into the weekly
13 period.

14 SESSION CHAIR PORTIER: Time is a-
15 wasting here.

16 DR. HENDLEY: Yes. Okay. And so we
17 had weekly sampling during April to July and then
18 again went back to the two-weekly schedule for
19 the rest of the year and there were also sampling
20 regimes with 17 samples, nine and six during the
21 year.

22 The sampling design that was used in

1 this piece of work by Research Triangle
2 International was a series of windows were
3 created and the approach was to take one sample
4 in each simulation, one sample point within the
5 window with replacement. Each day in the window
6 had an equal probability of selection for all
7 1,000 simulations.

8 And so you took a random day within
9 the week. You moved to the next selection week,
10 took another random day. And the reason for that
11 is because that is actually the instruction that
12 was given to the plan operators, not that they
13 had to go every Tuesday, because that was an
14 unfair burden but they were to take one during
15 the calendar weeks, following that schedule in
16 the table.

17 So for each simulation there was a
18 linear interpolation between the sampled points
19 to come up with a 365-day profile and from that,
20 a 90-day rolling average was created for the days
21 and the maximum simulation 90-day rolling average
22 was obtained.

1 And the difference between the
2 simulation 90-day maximum and the true maximum
3 for each of those community water system years
4 was recorded and then you had a set of maximum
5 simulated to maximum and that was worked on as a
6 full data set and as data subsets based on the
7 source-type. So that was the background to how
8 we processed the data for that piece of work.
9 And I realize you need many hands to hold all the
10 pieces of paper.

11 DR. YOUNG: So the results are in this
12 set of slides?

13 DR. HENDLEY: The results are
14 summarized on slide 12 of the presentation. The
15 90-day exposure slide, which is entitled
16 "Sampling Frequency and Confidence; 90-day
17 Exposure."

18 DR. SIELKEN: This is Dr. Sielken.
19 There is an analogous set of answers in the other
20 handout that you had that I provided that was
21 done using the procedure that I am going to
22 describe later. But there are also additional

1 numerical results for that type of analysis.

2 DR. HENDLEY: And of course, the full
3 background to this, Dr. Young, is in the Chen, et
4 al. 2009, the evaluation of sampling frequency
5 alternatives, which is in the docket.

6 SESSION CHAIR PORTIER: And I think
7 the key conclusion here is that when you use that
8 methodology to look at reduced sampling schemes,
9 so going from roughly 25, 26 samples in a year
10 down to six or nine samples and showed that by
11 that same methodology you got the same
12 distributions with fewer samples.

13 DR. HENDLEY: Precisely. Precisely.
14 Thank you. Any further questions on that one?
15 Okay.

16 Okay, the last one of my presentation
17 before Dr. Sielken refers to slide number 14 in
18 the presentation that I made and it is entitled
19 "Sample Frequency, Shorter Exposures." This one
20 will be quicker, Mr. Chairman.

21 The key points of it, unlike the last
22 one where we started off with atrazine monitoring

1 program frequency, which was basically seven days
2 apart, this is using daily data sets. And I
3 should say, there is one other data set we
4 haven't been specific about and Dr. Gilliom can
5 tell you more about it, and that is a set from
6 2001 for Lake Perry, which was done by Blomquist,
7 et al., it is submitted, it is in the EPA White
8 Paper and that had daily data for a large static
9 body. And I realize that we never actually
10 mentioned that here.

11 So as you remember, we had finished
12 data from a community water system in Missouri
13 that was daily or near daily. And we had daily
14 or near daily data from the Eco program and the
15 Heidelberg programs.

16 So for each source of data for each
17 year, we took the measured daily or near daily
18 data. We filled in any gaps with linear
19 interpolation to create a 365-day time series and
20 we identified peak and we computed point
21 estimates of the 95th and 99th centile daily
22 value. And those were the true ones against

1 which we compared.

2 DR. YOUNG: So how were those
3 percentiles estimated?

4 DR. HENDLEY: Dr. Chen?

5 DR. CHEN: This is Wenlin Chen,
6 Syngenta.

7 The percentile actually are calculated
8 based on the daily chemograph generated. We
9 looked at the maximum each year at each site.
10 You have a sequence of events and you keep the
11 maximum as a peak concentration for that year for
12 that site and then calculate those so the 90th
13 centile and the 99th centile.

14 DR. YOUNG: So you used, basically the
15 rate data and took the percentiles of the data?

16 DR. CHEN: Right, yes.

17 DR. YOUNG: Okay.

18 DR. HENDLEY: So again, using that
19 365-day time series for that source of data for
20 that year, we used the same simulation approach
21 using the window approach that we have just
22 discussed. And so for each resulting simulation

1 of those one thousand simulations, a linear
2 interpolation between the sample points generated
3 a 365-day profile as before and the peak and 95th
4 and 99th centile of daily values were obtained
5 from that.

6 And then from each distribution of a
7 thousand runs, the example in the handout that
8 was given, this was from Dr. Mosquin, shows the
9 mean, the peak, and the 95th centile daily values
10 and their percentage deviations.

11 So has that clarified the data
12 processing for that?

13 DR. SIELKEN: This is Dr. Sielken. Dr.
14 Mosquin's handout that he is referring to are the
15 two separate pages that were put in the docket
16 from Dr. Mosquin?

17 DR. HENDLEY: Yes, the last two in
18 there.

19 SESSION CHAIR PORTIER: And the
20 conclusion from this, again getting back to the
21 conclusions of this exercise, is that when you
22 compared a once-a-week sampling to your overall,

1 you tend to underestimate the maximum by 20
2 percent, 20 percent to 80 percent for Missouri,
3 and 1.1 to 2.6 multipliers for the others. So as
4 we would expect, you are underestimating the
5 maximum. What you were doing here was estimating
6 the multiplier between the maximum between the
7 sample distribution to the real. Being able to
8 say, if I had sampled once a week during the
9 season and used that to create my profile, I
10 would underestimate the maximum by 20 to 80
11 percent. Right? I mean, is that kind of the
12 conclusion?

13 DR. CHEN: These systems are not --
14 sorry. This is Wenlin Chen. You mentioned the
15 three systems. One is St. Louis which is a true
16 drinking system, the other two are at the Ohio
17 River and the eco that is not drinking water.
18 That is just ecological water system.

19 SESSION CHAIR PORTIER: And you get
20 the performance with the drinking water profile
21 and the worst performance with the well water
22 profiles, as we would expect.

1 Dr. Heeringa?

2 CHAIR HEERINGA: Steve Heeringa.

3 Paul, there is a chemograph that is illustrated
4 on this handout sheet. Is that typical of one of
5 these water systems? For example, you are using
6 site-specific, year-specific data. So you have
7 seven years for this Missouri finished water
8 system. What do those chemographs look like?

9 DR. HENDLEY: Paul Hendley. The
10 Missouri chemographs have a low maximum value but
11 they are actually quite spiky. In a way, quite
12 surprisingly spiky. So some of the peaks appear
13 to be of the order of maybe three or four days.

14 DR. CHEN: Wenlin Chen. I just wanted
15 to add to that is that we are looking at the
16 ratio, not the absolute of the peak. So when you
17 look at the ratio, it should give you, it cancels
18 out where it is really spiky or not spiky.

19 CHAIR HEERINGA: Steve Heeringa. My
20 concern is that the spiky problem is the tough
21 one. And I assume the Heidelberg data, which are
22 Honey Creek and Rock Creek, that those are spiky

1 data as well because those are agricultural
2 drainage, mostly.

3 DR. HENDLEY: Especially for the two
4 that you have selected, which were Honey and
5 Rock, which were about 35 and I think 130 square
6 miles.

7 CHAIR HEERINGA: Thank you.

8 SESSION CHAIR PORTIER: Paul, scroll
9 down so people can see the image Dr. Heeringa was
10 talking about. I think it is further down on
11 your slide. Isn't it?

12 DR. HENDLEY: I think it is on one of
13 the others, yes.

14 SESSION CHAIR PORTIER: There it is.

15 DR. HENDLEY: There you go.

16 SESSION CHAIR PORTIER: And the red
17 lines identify the sampling bins, the periods for
18 the windows.

19 DR. HENDLEY: Absolutely correctly.
20 So what you are doing is you are getting the
21 computer to pull a sample from each of these
22 windows.

1 So with that, if there is no further
2 questions from the hydrology group, we would like
3 to turn to the discussion for underlying -- Where
4 is your presentation? And this underlies slide
5 13

6 DR. SIELKEN: This is Dr. Sielken.
7 Thank you, Mr. Chairman and the rest of the
8 panel.

9 This is some supplemental explanation
10 to go with the short handout that was part of the
11 docket yesterday. There seemed to be a missing
12 link in the middle of it. And since it was no
13 simulation and no trickery or anything like that,
14 I wanted to make it clear the step-by-step
15 procedure that I was going through and also
16 differentiated a little bit from some of the --
17 slightly different than the Mosquin procedure,
18 although our procedure and our results ended up
19 being within ten percent of each other. So they
20 were very close, even though they were slightly
21 different.

22 The procedure that I applied both to

1 all 202 CWS's as well and that was on a multi-
2 year profile, I also applied to the St. Louis --
3 I'm sorry. I wasn't supposed to say that. The
4 Missouri community water supply system, which was
5 close to daily data. I did that both yearly in
6 groups and multi-year. And I also applied that
7 to, the same system, to the almost daily data in
8 the Heidelberg data sets, the Honey, the Rock,
9 Sandusky, and Maumee.

10 In all of those cases, the procedure
11 was as follows. And it is almost identical
12 whether you use linear interpolation or step-
13 wise. So that is not really a big deal.

14 You start out, at least for data sets
15 like this where you followed this nearly weekly
16 or nearly daily sampling. It is a fairly dense
17 data set, as shown on the top of this slide. The
18 slide underneath it is the linear interpolation
19 and that is where we started. And the only
20 modeling that was done was just that linear
21 interpolation. There was nothing else that was
22 simulated.

1 SESSION CHAIR PORTIER: And for those
2 who can't read it, that is about 13 years' worth
3 of time series data for one site that you are
4 showing there.

5 DR. SIELKEN: Yes, that is correct.
6 We had a variable number of years in CWSes. Most
7 of them had around ten years. Well, there were
8 351 profiles that were 13 years long; 351 CWS
9 years came from 13-year profiles. So that was
10 13-year profiles and seven-year profiles were the
11 most common length of profiles.

12 From this linear interpolated profile
13 for multi-years capturing your variability, I
14 went through and overlaid a grid of seven days
15 wide. A window, a seven-day wide window. And
16 then picture of course that seven-day window is
17 not to scale. But you know, put a grid over it
18 of seven days and then started at the beginning
19 of the profile on Monday, went to the next
20 Monday, took another -- and this is in the seven-
21 day sampling.

22 We actually did the testing because

1 you were interested in perhaps changing the
2 frequency of sampling. We also looked at two-
3 day, three-day, four-day, five-day, six-day,
4 seven-day, weekly, bi-weekly, tri-weekly, and
5 monthly. So we looked at all of those profiles
6 in exactly the same way that I am going to show
7 here and I will use as an example the seven-day
8 spacing. So analogous to what is going on now.

9 Given the linear profile, we overlay
10 a grid of the sample spacing here seven days
11 apart. Start systematically with Mondays and
12 then go to the next Monday and so forth and just
13 march through that entire profile every seven
14 days, starting with a Monday, record those
15 values, take a linear profile between those seven
16 day values -- no. Sorry.

17 Take those seven day values, find the
18 max, and then compare that max to the original
19 profile max, the data profile max. So when we
20 are looking at acute for one day, we just take
21 those seven-day spaced apart samples, compare the
22 max in that set of samples to the max in the

1 original profile. So there is no simulation in
2 there.

3 I did that starting on Monday,
4 starting on Tuesday, Wednesday, Thursday, you
5 know, all the seven possible starting points. So
6 there were seven sample maxes to compare to the
7 overall data profile max. And you can see the
8 variability in those numbers on this profile.
9 You know, 0.97 for Mondays, 0.96 for Tuesdays.
10 Obviously, one of those was going to hit it and
11 it was Saturday in this example, sort of.

12 I took the average of those seven
13 numbers and that is what I recorded as the single
14 number for that CWS is a ratio of the sample max
15 to the data profile max.

16 And now this next slide is the new
17 one. And that was to say what did I do with
18 those 202 numbers? Well, first of all, that is
19 what I worked with was those 202 numbers; one for
20 each CWS, just a comparison of the sample max to
21 the profile max. I took those 202 numbers and
22 found the percentiles of those 202 numbers. So

1 there was no simulation of anything in there.

2 And the little histogram here in the
3 center is just to hopefully eliminate confusion.
4 If there was a grid, and all of these ratios for
5 seven day spacing and trying to target an acute
6 daily value or a daily value, the ratios between
7 the sample max and the true max ranged from 0.75
8 at the low end up to one. There was 18 from 0.75
9 to 0.80; 31 in the next bin, and so forth.

10 So they were not very widely spread.
11 The worst case was around 0.75. So you were only
12 off by a quarter, 25 percent, using seven-day
13 sampling to estimate the ratio between a max one
14 day and a profile one day. So for a one-day
15 target, you can use a seven-day sampling and be
16 within 25 percent.

17 Dr. Lee?

18 DR. LEE: For the ones where it is you
19 are sampling say every seven days, did you
20 average across the possible seven starting days
21 to get the figures in the table?

22 DR. SIELKEN: Yes, I did.

1 DR. LEE: Okay, thank you.

2 DR. SIELKEN: So, it was the expected
3 performance of the sampling plan.

4 Okay, that was probably the slide that
5 was most missing from your explanation before.

6 That set of percentiles computed from
7 the 202 values was tabulated in your handout for
8 both one-day sampling, of course that would have
9 been perfect; two-day sampling; three-day
10 spacing; all the way up to 28-day spacing. So
11 this is just a table repeating the analysis for
12 each sample spacing and then just recording the
13 percentile.

14 SESSION CHAIR PORTIER: If I can
15 interpret this and then if you look at the last
16 column, 28 days, it says if instead of sampling
17 every day you sample once a month, kind of on
18 average you are going to whatever it is, 22
19 percent below the kind of in the long run, you
20 are going to be 22 percent below the true daily
21 maximum. Right?

22 DR. SIELKEN: I'm not exactly sure

1 where you are seeing 22 --

2 SESSION CHAIR PORTIER: I am looking
3 at the 50th percentile. I'm sorry. The median.

4 DR. SIELKEN: Oh, at the 50th
5 percentile. Okay. Going right across here,
6 0.7548, you are about 25 percent below.

7 SESSION CHAIR PORTIER: It is 0.79.
8 So it is like 21 percent.

9 DR. SIELKEN: Well okay, yes.

10 SESSION CHAIR PORTIER: You can't read
11 it from there.

12 DR. SIELKEN: Knowing that tables are
13 hard to read, regardless of the magnitude, I put
14 a little picture in and you can't read that
15 either but it gave me the idea that as you varied
16 the sample spacing between one day, which gave
17 you perfect results, to 28 days, how did your
18 ratio drop off at the 95th? Well, the orange, if
19 you can see orange is in the middle, and that is
20 the 95th, there is the 97.5 and 90 below it. So
21 those three profiles of interest, how they change
22 with sample spacing.

1 And notice that if you don't like
2 pictures, I put it in numbers again. And they
3 are saying that if you take a seven-day sample
4 spacing, keep your current spacing, you are
5 within a quarter for single-day target within 20
6 percent for a three-day target, and so forth.
7 Notice that for a 90-day rolling target, you are
8 almost there all the time.

9 So this is showing that regardless of
10 your target, really, you are doing quite well
11 with the existing plan. Now this was to test the
12 sampling performance.

13 What happened? Oh, well, I reached --
14 well how silly. I want to get back to the
15 folders. Where is the folders? Yes, here we go.

16 That showed that you could stick with
17 the current sampling plan and for finished water
18 or even doing the same example with the
19 Heidelberg Eco, getting approximately comparable
20 results. And those were shown in the first
21 handout that I gave, put on the docket a couple
22 of days ago down here. I apologize here.

1 We did that same procedure as Dr.
2 Hendley mentioned, we did that not only for the
3 202 CWS collectively, we also split them up by
4 groups, flowing, mixed and static. We got pretty
5 much the same results. You can see a comparison
6 there between what we got for all the CWS
7 together with what we got for the different
8 partition. That is in the handout that you got
9 on the first day from me, which is going to look
10 like that.

11 And then because this was the 202 CWS,
12 which is a really strong database for capturing
13 year to year variability and the differences
14 between CWS in Indiana, Illinois, Ohio, Texas,
15 you know, covering that entire region and the
16 different year effects.

17 And of course, if you look at a CWS,
18 there is a lot of year to year variability. Then
19 going from that set as a test case to another set
20 that didn't hardly involve the linear
21 interpolation because you had almost daily
22 sampling, which is the CWS set in Missouri, which

1 is shown in this slide. Yes, well if I do that
2 then I lose where I was.

3 You can notice these numbers down
4 here. The lowest number in that table is, you
5 know, for the hardest target, which is single
6 day, those numbers are about a third. The lowest
7 number there is 65 percent or something like
8 that, 60 percent. That means you are off by 40
9 percent, not even a factor of two.

10 Okay, also you know, this was for
11 almost daily sampling of finished water. This is
12 the Heidelberg data set. Again, the two worst
13 cases and again, this is not drinking water but
14 an ecosystem, your lowest number is around 40
15 percent. So you are off by that much. So again,
16 right around at worst a factor of two.

17 DR. HENDLEY: And just if I can, this
18 is Paul Hendley again, that was why having worked
19 from the strength of the temporal and spatial
20 VMP/AMP database and from the strength of the
21 daily database and coming together and finding
22 the results were coherent was one of the points

1 we made earlier.

2 SESSION CHAIR PORTIER: So do we have
3 any follow-up questions of Linda or Dr. Lee? Dr.
4 Heeringa.

5 CHAIR HEERINGA: I just want
6 confirmation that the two sets of analyses, the
7 one done by RTI and then the one done by Sielken
8 and Associates, Bob you just used systematic
9 sampling throughout the year. The other just
10 used the random draw within these time windows
11 that have been set out under the plan.

12 DR. HENDLEY: That is correct.

13 CHAIR HEERINGA: That is the primary
14 difference between your treatments of these same
15 data?

16 DR. HENDLEY: Yes, that is primarily
17 the difference. The only other difference is
18 they looked at every year individually. And I
19 did, too, but I did a multi-year profile.

20 There was one other comment I wanted
21 to make because you asked it yourself, Dr.
22 Heeringa, was what durations. In the first part

1 of the handout, we looked at, you know, gave the
2 full numerical distributions of characteristics
3 for one day, ten day, 30 day and 90 day rolling
4 averages. We gave the concentrations, the
5 distribution of concentrations, the distribution
6 of rolling averages. We also addressed the
7 question that you raised was what about how many
8 days in a row did you exceed certain levels.

9 And there was, in that handout, I will
10 just leave it here, in that handout, there are
11 tables that do for the daily profiles the
12 concentrations and then there is just this one
13 page on page five in that handout where we did
14 look at duration, number of days above specified
15 values. And I only have the one day and the ten
16 day in here. But I can tell you that at the 99th
17 percentile, there was no CWS, none of the 202 CWS
18 for finished water that had durations above
19 twelve and a half for more than a day. And so
20 there was no duration above twelve and a half.

21 Obviously at the extremes there was a
22 little bit, I mean, there was more duration at

1 the max but there wasn't, you know, at the 99th
2 percentile, there was none for the day, 10-day,
3 30-day, 90-day, there were no durations above
4 that target value of like twelve and a half.

5 SESSION CHAIR PORTIER: Okay. Yes,
6 Dr. Gilliom?

7 DR. GILLIOM: I just want to make a
8 general point that we will probably come back to
9 in discussing the charge questions but it is
10 important in just interpreting all of this.
11 There is a tremendous number of numbers. And you
12 can generate tons of numbers from synthetic
13 sampling experiments and everything.

14 I just want to make the general point
15 that the importance of each sampling experiment
16 to a specific objective questions depends
17 entirely on how well the simulated truth
18 represents actual truth.

19 So, if we get to a problem where we
20 are looking at a very short-term occurrence like
21 daily, we have to be sure the starting point is a
22 confident estimate of the true daily

1 distribution. And there is a lot and I don't
2 even intend to jump into every individual
3 experiment that has been done by Syngenta or EPA
4 but every one of them has a little different
5 twist on how truth was defined and what time span
6 it is relevant to.

7 So my general point is, there are so
8 many possibilities here we are going to have to
9 get that objective very clearly defined so that
10 we can then evaluate which one is the right one
11 to use.

12 DR. SIELKEN: I agree with Dr. Gilliom
13 that establishing the truth is an important
14 thing. I would point out that when we did the,
15 we took the 202 CWS and took the linear profile
16 as a starting point, my intention was not that
17 that necessarily captured the max within the
18 water that was actually there but if I took those
19 values which are a representation of reality,
20 took that as a reality, it may not have been
21 quite as much of a reality as some people would
22 have wanted if they were to sample more often.

1 But with that as the reality, given
2 that reality, how well did you do with your
3 monitoring program? So that was really the issue
4 was the ability or the performance of the
5 sampling. And that is also why we turned to the
6 more daily profile values and tested it there.

7 Thank you.

8 SESSION CHAIR PORTIER: Paul, you want
9 to wrap up? Final comment? No.

10 Dr. Akana had a question.

11 DR. AKANA: A small point that you can
12 clarify for me. What I understand correctly
13 though, this data treatment is equally valid on
14 say the raw samples that start much higher as
15 well as lower. For instance, the raw data here
16 mostly the points are like three or under parts
17 per billion but the treatment is equally valid if
18 your dataset runs up to 30?

19 DR. SIELKEN: Yes. Yes, because we
20 were looking at ratios between the sample max and
21 the true max, that ratio would be invariant to
22 whether we were going zero to three, zero to 30.

1 You are absolutely correct. It would be
2 applicable.

3 DR. AKANA: But that does mean if your
4 estimate is say 20 percent under-represented, for
5 three, it is 20 percent and for 30 it is 20
6 percent.

7 DR. SIELKEN: Yes, that is correct.

8 DR. HENDLEY: So Mr. Chairman, I would
9 like to wrap up. I will make one comment on
10 that. Of course, that is a correct statement
11 that as we pointed out before, if you are trying
12 to understand the variability for drinking water
13 values, you are best off using drinking water
14 data where it is all possible. But the raw data
15 was a great way of getting a handle on
16 understanding variability.

17 However, we do appreciate the time you
18 gave us to try and clarify some of these issues.
19 So thank you very much. We appreciate it.

20 SESSION CHAIR PORTIER: Thank you.
21 And now Nelson Thurman and Mary Frankenberry. I
22 always get her last name wrong. I just know her

1 as Mary.

2 And also at the table is Don Brady,
3 the vision man. And of course we are way beyond
4 my half hour target. This is the last half hour
5 before our discussion.

6 MS. FRANKENBERRY: Thank you. And
7 again, I can go quickly I hope. Our slides I
8 think are a lot simpler than Syngenta's. We did
9 not get their handouts until one of them this
10 morning and would like to get them from Joe
11 Bailey, I think, certainly before the end of the
12 day.

13 Hopefully with these, it appears that
14 they have done at least in one or two of their
15 exercises something very similar to what we did
16 and I am hoping that these will be easy to
17 understand.

18 Step one, we took a sample chemograph.
19 That is what we get from the field, 30 to 35
20 samples. We augmented it linearly to 365 days to
21 make a true or reference profile that we are now
22 calling true.

1 What we got in step two we would like
2 to consider reality. It could have been instead
3 the Heidelberg dataset that would have started
4 with, we wouldn't have had to do as many
5 interpolations but this is what we got and
6 considered as true.

7 From that we sampled this true profile
8 or what we consider reality out in the field.
9 Let's just say we will look at the example of
10 sampling every four days. We took this -- this
11 is what we do in the field. We may sample every
12 seven days, actually in the AMP program. For
13 this example, try four days.

14 What we get from number three then, is
15 what we get our as our sample dataset from
16 Syngenta or from wherever we receive a dataset.
17 And that will have 90 some values, perhaps or 30
18 to 35 if it is from the AMP.

19 For the purpose of the exercises then
20 we augmented this new sample chemograph up to 365
21 days. In some runs we ran step-wise, others
22 linearly but what we presented in the paper were

1 linear interpolation.

2 For that new, that sample that was
3 interpolated from step four, we calculated, as an
4 example, three-day running averages, starting
5 days one to three, two to four, all the way up to
6 363 to 365 days. We did rolling three-day
7 averages there.

8 In step six, we took the maximum
9 three-day running average from this re-sample or
10 the first re-sample, if you will. We set it
11 aside into the bootstrap pile and that is what we
12 will call it without the acronym there.

13 (Laughter.)

14 MS. FRANKENBERRY: I actually made
15 myself laugh last night and then forgot about the
16 public record.

17 (Laughter.)

18 MS. FRANKENBERRY: In step six, we
19 repeated this 4500 times with replacement until
20 our bootstrap pile contained four to five
21 thousand maximum three-day running averages. So
22 what we have there is a distribution of maximum

1 three-day averages, three-day running averages
2 that was derived from sampling every four days.
3 That is our bootstrap sample of maximum three-day
4 averages.

5 And in step seven what we did then was
6 we spread it out. We looked at its range from
7 minimum to maximum. We looked at the 50th
8 percentile values, low percentiles, high
9 percentiles, and we compared these to what we
10 would have gotten from the so-called true maximum
11 three-day running average. What we were looking
12 for is how often we captured the true max and
13 when we did not, when underestimated it, how
14 often did that happen and to what magnitude to
15 what extent.

16 Those are those questions. I can come
17 back to that but just to show you, again this
18 graph isn't that easy to see but what you are
19 looking at there, each of these, look at number
20 four. That is the bootstrapped distribution of
21 maximum three-day averages sampled at four-day
22 intervals.

1 And we went from underestimating by
2 31.5 percent up to getting it right on with no
3 error. That is the range of our performance
4 there. We want to look down at, I think, number
5 13 was our best run or one of the best
6 chemographs. We went from minus two percent up
7 to no error. So that is a very narrow range and
8 we looked at how often. These are all again
9 maximum running three-day averages.

10 And I think in some of our, let's go
11 back up to this question. Do the highest runs
12 equal or exceed the true max? How much lower
13 than true are the lowest runs? And then if we
14 wanted to create an interval on a given CWS, let
15 me go back to this, from minus 30 to zero, that
16 is one kind of interval. If we wanted to look
17 down at our better ones, number 13, we go from
18 minus two up to no error. That is a kind of
19 interval in itself.

20 One of the questions that we will be
21 asking the panel is what do we do with these as a
22 whole? If it happens and this is totally

1 hypothetical, if our health effects people are
2 looking at a three-day average and they say how
3 well would we do if we sampled every four days,
4 we could say, I think on mean runs, the average
5 performance was about five percent under true.
6 Our lowest runs, I think, were on average about
7 13 percent under true for sampling every four
8 days on a three-day average.

9 Now we have asked them, can you live
10 with that if you would like a four-day interval
11 sampling strategy. The thing is we can look at
12 this and say we average 13 percent in the lowest
13 runs below true but we have some higher values
14 that were 30 percent under true. So do we want
15 to make a competence interval around our
16 performance here or do we want to take, run them
17 all as a whole, look at the lowest one percent of
18 all the CWS and say 99 percent will be at or
19 better than this kind of performance. I think
20 that is what we were getting at in asking for
21 advice on bounds for the population, what to do
22 with that, or can we produce a prediction

1 interval because we are looking at what we have.

2 But what do we expect on new systems?

3 Then when we go from here to
4 individual samples, I think we are relying on
5 asking your advice on things like the different
6 interpolation levels, which did make some
7 difference, we found, in how well we
8 underestimated or overestimated. It wasn't a lot
9 but I think with stair-step you can overestimate
10 more often than not. And I believe it is
11 possible to underestimate a little more in
12 magnitude but we didn't do a systematic look at
13 that.

14 That and any other methods that you
15 could, kriging, whatever that would help us on
16 the individual level. We are trying to go from
17 talking about bounds on something like this for
18 the population to then what do we do on an
19 individual level.

20 SESSION CHAIR PORTIER: Dr. Heeringa?

21 CHAIR HEERINGA: Steve Heeringa. You
22 bootstrapped this 4500 times but in a systematic

1 sample of 365 days, there are only 90 unique
2 samples. So are you not simply just at random
3 sort of getting an expected repetition of five of
4 these?

5 MS. FRANKENBERRY: We repeated, yes,
6 on purpose to get a larger number of samples so
7 that when we looked at the lowest one percent or
8 the highest one percent, we would have more
9 samples to deal with but definitely the finite
10 value for each of the running averages. And we
11 simply re-sampled more to be able to have more to
12 deal with.

13 CHAIR HEERINGA: There were sort of 91
14 or 92 unique values that could occur from your
15 sampling process in CWS?

16 MS. FRANKENBERRY: I think it is more
17 for four days because if you start from day one
18 to day three, then day three, two to four, three
19 to five, all the way up to 365, 363, it is
20 something like 365 minus three or four days,
21 something like that. I think the worst case is
22 with 90-day averaging. I think it is 365 minus

1 90. It comes around, something like that.

2 SESSION CHAIR PORTIER: Yes, Dr.
3 Gilliom?

4 DR. GILLIOM: Again, I think this will
5 come up later but just a comment briefly now
6 because of the point just made. And I think this
7 is meant as an illustration of a data analysis
8 process, more than like the final answer. So
9 this won't be meant to be particularly critical.

10 But to evaluate a short-term exposure
11 like this, the way the truth was created is not
12 appropriate, basically.

13 I am going to keep coming back. The
14 starting point in how we define truth is the
15 absolute most critical step in every one of these
16 experiments. Like here, truth on a daily basis
17 was created from samples that were 30 or 35 times
18 a year. It is missing many of the
19 characteristics of short-term fluctuation. So
20 when you simulate sampling from that, you are
21 going to do pretty well recreating what you
22 already got from a limited sampling.

1 So basically the underlying data used
2 to define truth has to be denser than the type of
3 time frame you are trying to evaluate. And that
4 is why you see so much work done on these
5 relatively few sights that have daily data. And
6 we will see this as kind of a recurring --

7 SESSION CHAIR PORTIER: This is Ken
8 Portier. Your underlying simulation model has to
9 be complex enough to capture that high resolution
10 variability.

11 DR. GILLIOM: Yes, you have to have
12 some basis to defend that your truth represents
13 truth for the timescale you are going to now
14 experiment with.

15 SESSION CHAIR PORTIER: I think most
16 people understand that.

17 MS. FRANKENBERRY: And we did
18 acknowledge that, I think, in the paper. Some of
19 the Heidelberg datasets were not quite 365 but of
20 course they were much better than 30 samples. So
21 and I think that was our next step in plans. We
22 just only got so far. I think, Nelson, did you

1 want to address it later?

2 SESSION CHAIR PORTIER: It doesn't
3 look like we have any additional questions. Mr.
4 Thurman, did you want to have some comments?

5 MR. THURMAN: Yes, actually I want to
6 bring us up to from, I am not going to say down
7 in the BS pile but from down in the weeds, I want
8 to bring us back a little higher elevation in
9 terms of we get into this discussion.

10 And first of all, I do want to
11 distinguish one area where we do not agree with
12 Syngenta on this. I mean, some of the contention
13 is the assumption is we should only be doing this
14 assessment based on finished water because
15 finished water through all the processes are
16 going to be more blended and smoothed out than
17 raw water.

18 However, the best data we see in
19 finished water is weekly sampling. So we don't
20 know what is happening in between. And I
21 actually was pulling up an example last night for
22 something else and it turned out to be a pretty

1 good example here. This is for one system in
2 Ohio in one year. The magenta are the raw water
3 samples. The dark blue triangles are the
4 finished water samples. And what you see is the
5 finished water follows the same type of pattern
6 we see in the raw water.

7 There is nothing in this that suggests
8 to me that we would expect the finished water to
9 be less variable on the days that weren't sampled
10 than we see in the raw water in this particular
11 system.

12 So this is why we are looking at as we
13 try to define the truth, what are the best
14 datasets out there to define the truth. And
15 those that have more robust sampling are what we
16 are going to work with.

17 The other thing that is interesting is
18 you look here, you see an early season shorter
19 peak and a longer season, a larger peak later in
20 the season. Very similar to the pattern we were
21 showing in the Missouri site. So this is not a
22 pattern that we would not expect to see in some

1 of the community water systems. And so as we are
2 going through the analysis, we are looking at
3 those that have more intensive sampling so that
4 we have a better start with what the truth is.

5 And actually the reason I pulled that
6 sample out in the first place is something Bob
7 Gilliom raised and something some other panelists
8 had asked. We have been talking about atrazine
9 and we are looking at total chlorotriazines. The
10 advantage of the AMP monitoring that Syngenta has
11 done is that they have measured not just atrazine
12 but they have measured the individual components
13 to get at the total chlorotriazines.

14 I was looking at Ohio because I know
15 there is simazine use in Ohio. So I wanted to
16 try to show you an illustration of a site where
17 we have got both atrazine and simazine detected.
18 And you can see the dark blue triangles here
19 happen to be the simazine pattern. The magenta
20 circles are atrazine and the triangles are the
21 total chlorotriazines.

22 This actually shows that simazine is

1 following the same pattern that we see with
2 atrazine but I think that is because it is also
3 being used on corn. In other areas of the
4 country where it has different uses, we may see
5 different timing.

6 We do have this data that we can test
7 that. We can start asking ourselves do we see a
8 different pattern with simazine than we do with
9 atrazine and what effect would that have on
10 there? So we do have that power.

11 Okay, so let's go back to where I was
12 hoping the discussion would kind of help us, and
13 I wanted to explain to the tox people why trying
14 to decide are we looking at one day short-term or
15 longer term and not knowing drives us buggy.

16 This chemograph shows the blue line is
17 your daily measurement at this site. This red
18 line shows that if we were looking at a four-day
19 average, this is what type of -- this is your
20 rolling four-day average concentrations. So you
21 see, there is still a pretty good influence of
22 the shorter day measurements in a four-day

1 exposure.

2 I started working on the 90-day
3 exposure and I got this far and I probably didn't
4 realize okay, I needed to go back and get more
5 data and then decided I needed to sleep more than
6 I needed that.

7 But what I wanted to show is the
8 magnitude. This data point here and moving along
9 starts here, starts whenever you get your first
10 90 days averaged in. So you can see these
11 exposures are muted, potentially missing this is
12 not going to have as big an impact on a 90-day
13 exposure period as it is on a four-day exposure
14 period. So that is why knowing what our exposure
15 window is, really helps us in terms of how we
16 decide and how we interpret the data. So I
17 wanted to put that in to keep in mind, as you go
18 along.

19 Now if we were to take a look at that
20 seven-day sampling frequency that I showed it
21 seems like weeks ago but I think it was the
22 beginning of the week, this is the red line is

1 the four-day rolling average profile you see
2 estimated with all the daily values. The blue
3 line here is that same four-day rolling average
4 profile estimated with the weekly sampling points
5 that you saw in that previous slide.

6 So this is kind of what we are looking
7 at. We see more of a difference, even on the
8 shorter term averages, depending on the sampling
9 frequency than we would otherwise. So this is
10 the context I want you to think about as we get
11 into these questions. And with that, I am not
12 going to throw any more slide at you.

13 SESSION CHAIR PORTIER: Dr. Akana?

14 DR. AKANA: I have a late thought for
15 you. In the HPA world -- Well, first of all, our
16 small group here decided that a one-day exposure,
17 an acute hit is probably going to be okay with
18 atrazine. But in my personal view in the HPA
19 world, a hit say the third cycle away, so you get
20 a hit on the first cycle and if you get a little
21 hit on the third cycle, we are verging into this
22 where you get an extra effect on that third

1 cycle.

2 So now I am interested in little
3 clusters of little spikes. So up one day, down.
4 And then say six days later there is another one
5 day little up and down spike. That, as I
6 understand it, would not be picked up by most
7 sampling of finished water because of the way the
8 water is processed. But if that actually reached
9 -- Well, in the lab you can do that.

10 It can be just as deleterious and
11 verging into an episodic repeated exposure, which
12 is one spike of chronic. Chronic is not just one
13 up-peak and sustained of say atrazine. Little
14 spikes can be bad, too.

15 Now I am wondering if in your work you
16 can detect clusters of little spikes.

17 MR. THURMAN: Boy, that just made
18 things --

19 If you sample frequent enough, yes.
20 But that gets back to how frequent do you need to
21 sample. And if I go back, if you are looking at
22 something like this, even a creation -- but you

1 can start seeing that. If we say, and I am
2 going to use 20 just as an example and please
3 don't take that as this is what we are looking
4 at, but you can start to estimate how often do we
5 encroach that. And once again, how well we can
6 estimate that. The frequency above a certain
7 threshold value or a certain averaging period
8 threshold value, we can estimate that. It
9 depends on how frequently we have to sample to do
10 that. So, it can be done.

11 SESSION CHAIR PORTIER: I wanted to
12 make the point, too, you know, the spikes can be
13 artificially generated by lifestyle. So suppose
14 the background your tap water is a 20. On day
15 one half of your two-liter is from tap water. On
16 day two you are drinking bottled water. On day
17 three you are drinking tap water again. You have
18 just created that double pulse that you are
19 looking at. And so from EPA's point of view,
20 there is a lifestyle that has got to be
21 integrated into this and how people get their
22 two-liter dose every day, it is not always from

1 this.

2 Dr. Heeringa?

3 CHAIR HEERINGA: Steve Heeringa. For
4 Nelson, you look at this double peak pattern
5 which we have seen, particularly in some of the
6 agricultural drainages. Is this typically the
7 result of pre-emergent and post-emergent
8 application of atrazine or is it the result of
9 random rate of all events following application?

10 Because there is information. If it
11 is pre-emergent/post-emergent, you pretty much
12 know planning time and application times, in
13 terms of intensive sampling. So how much do we
14 know about that?

15 MR. THURMAN: I may give you a little
16 more complex answer. I mean, it could very well
17 be the result of when the farmer is getting out
18 of the field in relation to the rainy period.
19 And it is a conjecture because I don't have the
20 rainfall data at this point. It could be that
21 you had some initial planning going on. And so
22 you had some initial atrazine applications for

1 the short -- then you get a rainy period. And so
2 the farmer could not get back out in the field
3 until later. And then you see the second one
4 coming later.

5 It could be there is a difference in
6 intensities of the rainfall events that you see
7 here. This far apart suggests that you had two
8 different application periods. And it could be
9 for any number of reasons. A lot of times what
10 we have seen is that it is weather-related in
11 terms of how much can the farmer get out before
12 the rains and when do the fields dry up enough so
13 that they can get back out again?

14 SESSION CHAIR PORTIER: Dr. Krishnan?

15 DR. KRISHNAN: I just want to add to
16 the discussion that the spikes and their
17 relationship to the hits, I mean something that
18 is in-between is the internal dose measure. And
19 so these spikes may not necessarily translate to
20 the spikes of the appropriate dose measure in the
21 body that drives the sequence of events.

22 Given the rate of absorption and so

1 forth, the appropriate dose surrogate tends more
2 like the total chloro products. So I think one
3 of the focus would have to be, well essentially
4 because you can relate those effects more closely
5 to those internal dose measure, rather than to
6 the external spikes and the internal dose measure
7 would be more on the early end of the curve in
8 rating these.

9 And one of the focus would have to be
10 considering the integration of the drinking water
11 input with the PBPK model so that some of the
12 dose metric profiles can be evaluated in the
13 context of the detail evaluation as they go
14 forward. I think that would certainly add to the
15 science basis of qualities evaluations.

16 SESSION CHAIR PORTIER: Excuse me. I
17 have 10:17. We will take a 15 minute break and
18 then we will see if my gamble of increasing
19 understanding reduced the uncertainty in the
20 discussion time.

21 We will return at 10:35.

22 (Whereupon, the foregoing proceeding

1 went off the record at 10:18 a.m. and
2 resumed at 10:38 a.m.)

3 SESSION CHAIR PORTIER: Mr. Thurman,
4 I guess you are reading the questions. Hey, we
5 are not on question 1.9 anymore. Okay, Dr.
6 O'Byrne?

7 DR. O'BYRNE: Could I just ask one
8 very brief question? I was very surprised at
9 your graph that you plucked out last night from
10 wherever that the level of atrazine in the
11 finished drinking water showed the same profile
12 as raw, if I understood it properly. And you
13 sort of used that as evidence to criticize
14 Syngenta for focusing on finished water. I may
15 be misinterpreting this.

16 I am absolutely amazed that you see
17 the same profile because it depends on where that
18 finished water came from. I mean, was it a big
19 pool? A small pool? Because I would thought
20 there would have been a massive dilution of
21 anything.

22 MR. THURMAN: And I am not sure I

1 would call it a criticism. I think it is a
2 distinction between the way we look at things and
3 the way we interpret things. We have some
4 smaller community water systems that don't have
5 much of a holding period where you do see the
6 atrazine moving through and unless you have
7 sufficient carbon filtration, the atrazine will
8 continue to move through the system.

9 Some of the smaller systems I think
10 you heard Alan Roberson talk about that in the
11 public comments, they do try to treat. And some
12 of the systems we do see where the treatment is
13 knocking down the atrazine levels, sometimes
14 because carbon filtration is expensive, they
15 don't necessarily have it all year round. They
16 try to time it as best as they can. Sometimes
17 they get it, sometimes they miss.

18 Sometimes you see in some of the
19 systems where for the most part it is down but
20 then you will a spike coming through. But there
21 are a few systems that we are looking at that do
22 have a similar profile to what we see.

1 And the point we are making is we
2 don't necessarily want to wholesale right off
3 what we think are some valuable robust datasets
4 because they are not finished water sets. It is
5 what Bob Gilliom is talking about, how you
6 defined the truth. And if we have the robust
7 data sets that have sampling patterns and shapes
8 and patterns that are similar to what we are
9 seeing in these community water systems, we think
10 those are still very valuable. In fact, more
11 valuable to develop our statistical analysis and
12 the approach we take to evaluating the monitoring
13 strategies because they do capture that frequency
14 that is smoothed out when you have weekly
15 sampling or less frequent sampling.

16 So that was the point I wanted to try
17 to make in terms of that distinction. It is not
18 meant as a criticism but I think the reason we
19 are not writing off well water samples just
20 because they are not finished drinking water.

21 SESSION CHAIR PORTIER: This is Ken
22 Portier. It probably also reflects their

1 conservative nature. Right? So they look for
2 worst-case scenarios and they do their risk
3 assessment from a worst-case scenario, figuring
4 that that is going to be protective for everybody
5 else who are in better case scenarios from a
6 public health point of view.

7 Question 2.1.

8 MR. THURMAN: Okay. In conjunction
9 with the toxicological review presented in the
10 issue paper, the Agency has also discussed
11 methods for re-evaluating the sampling frequency
12 that is necessary for determining, with
13 confidence, concentrations of the pesticide in
14 water that sources drinking water. These have
15 included different methods for estimating
16 pesticide concentrations between known sampling
17 events and examining the performance of different
18 sampling strategies for averaging periods of
19 different durations. The Agency seeks feedback
20 from the Panel with regard to how the uncertainty
21 and variability in both the monitoring data and
22 in the toxicity data (i.e., the point of

1 departure) can be integrated to characterize and
2 to interpret the potential significance of
3 atrazine concentrations in drinking water.

4 Given the nature of the temporal
5 patterns of pesticide occurrence in surface
6 waters described in Section 5.2 of the issue
7 paper, including serial correlations from day to
8 day, periodicity in elevated concentrations
9 within seasons and from year to year, detections
10 below quantitation data, and uncertainty in the
11 shape of the pesticide distributions in surface
12 waters, what statistical approaches should the
13 Agency consider in determining confidence bounds
14 on exposure estimates from monitoring data?
15 Please comment on how the approach may vary
16 depending on the duration of concern.

17 SESSION CHAIR PORTIER: Dr. Young?

18 DR. YOUNG: Well, considering
19 confidence bounds on exposure estimates for
20 monitoring data, a key consideration is what is
21 being estimated. Now that sounds pretty simple
22 but here that seems to be quite a challenge.

1 So what you do differs on whether we
2 want to estimate a specific quantile given daily
3 data, or rolling average data, or if we want to
4 estimate the peak or whatever we want to do.

5 So, I want to put that out there first
6 because what we suggest will differ depending
7 upon what the final decision is.

8 So, if say I want to -- spikes seem to
9 be important. And if I want to estimate a
10 particular quantile, say the 99.99 quantile, the
11 99th percentile over the course of a period of
12 time, and let's suppose that is my goal for right
13 now. Okay? And if I want to say -- I think
14 another question that has to come up with this
15 particular atrazine, with this particular
16 application, is whether you want that for the
17 whole year or for a concentrated period of time
18 in which the concern is greatest. In other words
19 from prior to the start of planting to harvest or
20 sometime in that time frame. Because you know
21 that in most years, it is not as great of a
22 concern.

1 The easiest way to do such a sample
2 set in those confidence bounds is to know the
3 distribution. And then you take advantage of the
4 properties of the distribution to set confidence
5 intervals.

6 The problem is I don't think anyone
7 here is comfortable with knowing what that
8 distribution of values is. And when you do not
9 know that, then you are pretty much moving toward
10 non-parametric approaches. And I see that both
11 in that EPA does and Syngenta does and I think
12 that is the right approach.

13 Now, in order to actually use non-
14 parametric approaches, one of the big things that
15 comes up is sample size. And basically, you have
16 to have enough data if you want to estimate those
17 extreme quantiles with any precision.

18 So if you want a 0.95 quantile, you
19 need at least 20 observations, at least. The
20 standard there may be unacceptably large for that
21 sample size but that is a minimum and if you want
22 a 0.99, you need a hundred. Okay? That is just

1 the reality of what you have to have in order to
2 do a decent job.

3 And I saw a table of the sample sizes
4 in one of the Syngenta documents somewhere here.
5 And I put a similar one but I think -- and also
6 it is in the ILSI report that you referenced in
7 the Appendix A. I thought the Appendix A in that
8 report did a very nice job of outlining options
9 and certainly those could provide great guidance.

10 In that report, some simulation was
11 done and found that based on the same thing we
12 are seeing is interpolating among values and
13 dense datasets. And what they found was that
14 there was a tendency to overestimate the
15 quantiles, the extreme quantiles. So that is a
16 little conservative. And I believe the reason
17 that is the case is that inherent in these
18 methods is the assumption of a random sample and
19 the presence or correlation results in the
20 effective sample size being smaller than that
21 taken. And so we are actually pushing it out a
22 bit more.

1 And so I think work, that is a hard
2 problem, but I think work on how to actually
3 figure out what the effective sample size is and
4 refine those methods may be something you are
5 interested in but it is somewhat comforting from
6 the public standpoint that it is a conservative
7 estimate at the present time.

8 If we move to these rolling averages,
9 then the problem is further complicated because
10 normally we think in an independent sample, the
11 variance goes down. You just divide by the
12 sample size as far as the mean goes but you have
13 this positive correlation, which tends to keep
14 that variance inflated a bit.

15 And so that would need to be
16 considered in these methods. I have also thought
17 a little bit about using an extreme value theory
18 in this setting and especially on the rolling
19 averages because as soon as you begin averaging,
20 then you can begin to appeal to perhaps the
21 central limit theorem and if the data aren't too
22 skewed, then maybe you can begin to use some of

1 those ideas to reduce sample size. I haven't
2 fully explored that but I think it is something
3 worth looking into.

4 SESSION CHAIR PORTIER: Thank you.
5 Dr. Coupe is next.

6 DR. COUPE: Thank you. I think first
7 off I need to clear up something. This corner of
8 the table has been referred to as hydrologists or
9 hydrology. There is actually only two
10 hydrologists and two statisticians.

11 (Laughter.)

12 SESSION CHAIR PORTIER: That is an
13 important point, yes.

14 DR. COUPE: Yes, I spent an hour being
15 told what the difference between Bayesian and a
16 frequentist is. I still have no idea.

17 So my remarks are going to be, I am
18 not going to touch too much on the statistics but
19 mostly on the observations on the hydrology of
20 what we are talking about.

21 To begin so there is an issue on what
22 data should be used to determine exposure

1 assessments. There is data on atrazine
2 concentrations from the intake, the stream or
3 reservoir side, and then there is finished water
4 data. the U.S. EPA has decided to use the intake
5 values for assessment of human exposure.

6 The gentlemen from CropLife and
7 Syngenta suggested that the more appropriate data
8 to use to evaluate human exposure is the finished
9 water values. I can see both sides of this
10 argument as there can be considerable difference
11 between intake concentrations and the
12 concentrations in the finished water. However,
13 there are a number of studies showing that a
14 treatment plant effectiveness in removing
15 atrazine is variable depending upon many factors,
16 which includes the type of water, the organic
17 matter content or the pH, the type of treatment,
18 how well trained the treatment plant operators
19 are, the maintenance of the treatment. In some
20 cases atrazine survives the treatment process
21 relatively unaffected. Given this, I think it is
22 appropriate to use the intake values to estimate

1 the exposure to humans with the understanding
2 that this is a conservative estimate and that the
3 actual exposure may be less.

4 Given that, I do think Syngenta made
5 a valid point in bringing up the fact that the
6 community water system, that data that we are
7 shown by the U.S. EPA, would not have been used
8 for drinking water, as that plant selectively
9 pumps from the stream into a holding pond and
10 from there into another larger holding pond.

11 And I think this model is more common
12 in the small community water systems that take
13 directly from a stream. They don't have intakes
14 on the reservoir. And in this case, the
15 appropriate place to sample the water used by the
16 plant to evaluate human exposure, would have been
17 from the intake from the larger pond. The data
18 as shown gives a misleading impression of high
19 exposure from this community water system.

20 There are uses for these data, of
21 course, such as ecological exposure but it seems
22 inappropriate for the question being asked here.

1 The duration of concern makes a big
2 difference to the sampling strategy. If the
3 duration of the concern is very short, that
4 intensive sampling during expected high
5 concentration period is probably the only real
6 answer. But as the duration of concern
7 increases, the sampling intervals can be eased
8 and if the duration gets long enough, you can
9 actually estimate it from models such as WARP.

10 And in general, it seems that most
11 sites in the AMP program run by Syngenta, the
12 variability and the amplitude of the data are not
13 that great. If you look at page 94 where it
14 states in the White Paper from the U.S. EPA, it
15 states that 90 to 96 percent of the data are less
16 than three parts per billion. And Syngenta shows
17 pretty much the same thing in their response on
18 pages seven and eight.

19 Now this is good news in the sense,
20 especially when you consider these data are
21 biased with more frequent sampling during
22 expected periods of high concentration. In fact,

1 the AMP data suggests that there is only a subset
2 of some 27 or so of highly vulnerable community
3 water systems.

4 And to my mind, these sites probably
5 need to be treated separately and more carefully.
6 For the other sites, the 120 or so, the
7 concentrations are relatively low and don't
8 exceed the MCL often. But I suspect that is
9 because of the storage dynamics of these
10 reservoirs and these community water systems
11 probably have low --

12 Okay, what I wanted to say was that
13 these community water systems probably have
14 consistently low levels of atrazine in their
15 source water throughout the year because of
16 storage dynamics. And realistically, probably
17 more people are exposed to low concentrations of
18 atrazine for longer periods of time than they are
19 higher concentrations at shorter periods in time.

20 I thought of one other things when we
21 were talking, I think Dr. Akana brought it up and
22 a couple of other people were talking about the

1 spikes, and so far mostly what we have seen in
2 our chemographs are, I suspect just very small
3 sites. And so they show a very sharp one or two
4 peaks.

5 If you move to larger sites, you can
6 have multiple peaks. Especially if you take a
7 look at the Missouri data, you can see multiple
8 peaks during drinking water season kind of
9 depending on whether it is raining in Iowa or it
10 is raining in Missouri, or raining in Nebraska.
11 So you can have, in one community system, you can
12 have a number of small spikes but they can
13 consistently come through your system.

14 Thank you.

15 SESSION CHAIR PORTIER: Thank you.

16 Dr. Gilliom?

17 DR. GILLIOM: I'll just supplement,
18 rather than repeat some of what has been covered.
19 The first part of the question is related to what
20 approaches should be used to consider in
21 determining confidence bounds on exposure for
22 monitoring data. And so far we have talked

1 mostly about the use of site-specific data to
2 estimate those confidence bounds. And I just
3 want to make the point that there is also a range
4 of more indirect approaches using inference from
5 existing data. And there is basically probably
6 two categories of that. One you have heard a lot
7 about in relation to the sampling experiments of
8 taking these highly sampled data sets and driving
9 relationships that show how confidently we can
10 estimate a particular value with a given sampling
11 frequency.

12 So those are kind of categorical
13 things. The Crawford 2004 paper and the ILSI
14 appendix are good examples of that, which have
15 then been extended further by Syngenta and EPA
16 and they have plans to do even more.

17 So those give you a good initial
18 estimate in many cases of what kind of confidence
19 bounds to expect on any particular concentration
20 statistic. And you can re-do it for other ones
21 if you need to so it gives you an idea of how
22 much you have to worry about it.

1 The second category which we have also
2 just had mentioned here is the WARP model type
3 approach, which is really just a multiple
4 regression approach to relate basing
5 characteristics to concentrations and create
6 predictions. That is another indirect way to
7 make, based on the data we have already
8 accumulated from many sites, make estimates of
9 both the concentration statistic and the
10 confidence bounds for unmonitored sites.

11 And I bring those type of methods up
12 mainly, and particularly the second one on the
13 regression models is that a big part of the
14 approach here in the end is going to be to
15 identify the relatively small proportion of sites
16 that need the most intense energy applied to them
17 for the high sampling problems and so forth.

18 And this gives us a direct and
19 quantitative way of getting at that, both what
20 the expected concentration statistic will be and
21 what the expected confidence bounds on that will
22 be, which can now be done.

1 And then the second part of the
2 question is related to the duration of concern
3 and how the approach might vary. And I guess I
4 just want to reiterate the point that I think has
5 already been made a couple of times and it is
6 probably obvious at this point but the shorter
7 the duration of the concentration statistic, the
8 more intense data we need to get truth.

9 And it seems simple but it just
10 reiterates how much the answer that we come up
11 with on monitoring design is driven by how you
12 define very specifically the concentration
13 objective. So the Agency in the end is the one
14 who has to do that from what you all say but we
15 need to know the amount, the time frame, and the
16 confidence bounds required to meet the
17 requirements of the Agency and then you can
18 design around that.

19 SESSION CHAIR PORTIER: This is Ken
20 Portier. Just to clarify, when you say intense
21 data, you mean temporally dense measurement.

22 DR. GILLIOM: I will say in a more

1 general way, temporally intense in relation to
2 the sought concentration objective.

3 SESSION CHAIR PORTIER: Dr. Lee?

4 DR. LEE: I don't have too much to add
5 to what has already been said. I just want to
6 make two small points. One is that if we are
7 talking about confidence bands, I think it is
8 important to take into account some of the
9 sources of variability that we are not looking at
10 right now like measurement error.

11 You know, if you go and measure the
12 stream, if two different people do it, you are
13 going to get somewhat different answers probably.
14 And that sort of variability needs to be taken
15 into account, if you want to make a precise
16 confidence statement. And that doesn't
17 necessarily have to be estimated on a stream-by-
18 stream basis. I think we can learn a lot about
19 that sort of measurement globally and just apply
20 an estimate there. But that sort of variability
21 should definitely be taken into account.

22 And the second point I want to make is

1 that sort of follow on to some of what has
2 already been said, that the way you are going to
3 estimate the confidence band really depends on
4 what sort of model you are using to fill in the
5 gaps. Assuming you are not doing daily sampling,
6 you need some sort of model to say how we are
7 going to fill in the gaps and then the type of
8 confidence band is going to follow from that.

9 So I do want to disagree somewhat with
10 Syngenta's statement that we don't need modeling.
11 It is a model of some sort, even if we are doing
12 linear interpolation. That is a model. And so
13 either we need to sample daily or we need to use
14 some sort of model to fill in in-between. And
15 most likely, it is not a need to sample daily
16 because we can fill in in-between. But it
17 requires some model and that is going to affect
18 how we are going to compute confidence bounds.

19 SESSION CHAIR PORTIER: Thank you. We
20 will open it up to the rest of the panel.

21 Comments? Dr. Hayton?

22 DR. HAYTON: Do we have any idea of

1 how big a daily dose is the threshold of concern?
2 Because I am showing these chemographs showing a
3 hundred parts per billion. That is a hundred
4 micrograms and in two liters, 200 microgram daily
5 dose. Would that ring any bells in the BPA/BPH
6 signaling network? And to me, if it doesn't, do
7 we need to catch those peaks?

8 SESSION CHAIR PORTIER: Dr. O'Bryne?

9 DR. O'BYRNE: I don't think we have
10 any evidence at all that the small amounts have
11 any effect. They are orders of magnitude
12 greater.

13 SESSION CHAIR PORTIER: And I think
14 that has been said a couple of times before.
15 Maybe that is a subheading to our final report.

16 Any additional comments? Yes, Dr.
17 Heeringa.

18 CHAIR HEERINGA: Steve Heeringa. The
19 question may be for EPA. Thinking about the
20 simulations that you have done and that Syngenta
21 did and we get this sort of rough projection from
22 a simulation done on some periodic sampling to at

1 least truth as defined in an empirical data set
2 and we get factors like 1.5 or 1.24. How would,
3 in the context of where you set these limits, we
4 have uncertainty factors, is that sort of
5 uncertainty built into what you would think of as
6 your typical uncertainty factors or is this
7 something additional?

8 MR. THURMAN: Okay, we have wrestled
9 with how you do with uncertainty. I think you
10 have heard, for instance, that atrazine you have
11 heard the value is 12.5 and 37.5 used. When we
12 are looking at the weekly monitoring of these
13 community water systems, we have been looking at
14 how is that, because it is more intensive
15 sampling, we have been comparing that to a 37.5,
16 with less intensive sampling because there is
17 uncertainty in that we have been looking at the
18 12.5. So there is kind of a 3X that has been
19 used in that regard.

20 So it is possible that we might hold
21 that monitoring uncertainty, if you will, in as
22 part of the overall uncertainty or safety factors

1 that we look at.

2 DR. LOWIT: Anna Lowit. Just to add
3 to that, to sort of talk about the source of
4 where that comes from, as atrazine is regulated
5 under the food quality protection act, the FQPA
6 has a provision that requires the application of
7 the 10X. And that 10X accounts for both hazard
8 and exposure and that 10X value can be reduced,
9 as Nelson was talking about, the three, based on
10 information that the Agency looks like and the
11 science supports doing that. It can also be
12 increased.

13 So I just wanted to make sure that was
14 explicit of where that would be derived from.

15 SESSION CHAIR PORTIER: Dr. Reed?

16 MR. THURMAN: And by the way, this is
17 why you need hazard and exposure folks working
18 together on this.

19 DR. REED: I just want to put in a
20 caveat about the comparison, the water level and
21 then two liters per day and compared to the
22 animal study, there is a lot of "uncertainties"

1 because you have the interspecies variability
2 considered and also inter-individual
3 consideration. And so a straight comparison
4 probably is not very productive.

5 SESSION CHAIR PORTIER: Any additional
6 comments? Okay, I think we have gotten some good
7 comments, Dr. Young and the four. Dr. Heeringa?

8 CHAIR HEERINGA: Just one additional
9 comment. You know, I support what Dr. Young
10 indicated, too, and I think others that Dr.
11 Gilliom with regard to sort of differential
12 sampling over the years. I mean, if we think
13 about it simply as a sampling problem from a
14 frequentist's perspective, we would essentially
15 allocate sample to these intervals in proportion
16 to the standard deviation, the measures within
17 the intervals. And this can be adaptive, too.
18 In other words, you could start with a
19 periodicity and depending on the water system and
20 the information that is gleaned over time. So I
21 think rather than trying to hit a home run the
22 first time, try to get into the ballpark and then

1 think about refinement as you collect additional
2 data.

3 SESSION CHAIR PORTIER: And this kind
4 of was a question that came up as I was reading
5 this. This is Ken Portier.

6 When these community water systems
7 take these samples and process them, what is the
8 lag time between the sample and the number
9 actually being received back to the process, the
10 CWS manager? Is that hours, days or months?

11 DR. COUPE: All of the above.

12 SESSION CHAIR PORTIER: Really? What
13 is the median on that? Is that weeks?

14 (Laughter.)

15 SESSION CHAIR PORTIER: I didn't want
16 to max and min. I am more of a median. Is that
17 like weeks or days?

18 DR. COUPE: Oh, it is probably on the
19 order of days but there are some very large
20 systems that have large holding times and there
21 are very small systems that --

22 SESSION CHAIR PORTIER: Shift it off.

1 Excuse me. What was that? Weeks.

2 Because you know, -- yes, ma'am?

3 Please identify yourself.

4 MS. BISCOE: Melanie Biscoe. I am the
5 CRM or Chemical Review Manager for atrazine.

6 I think Syngenta has been talking
7 amongst themselves a little bit back here, and we
8 actually discussed this earlier this year. So
9 about ten days in the EPA, Syngenta monitoring,
10 CWS monitoring program, that you actually get the
11 numbers back.

12 SESSION CHAIR PORTIER: So this has an
13 impact for some of the things that statisticians
14 and samplers would like to say which is well, you
15 could do adaptive sampling. Once you start to
16 see it go up, you increase the sampling rate.
17 But if there is a ten-day lag and many of these
18 windows are 20 to 30 days wide, that methodology
19 is probably not feasible here. And then you are
20 stuck with kind of choosing a window of time and
21 increasing your sampling during that window of
22 expected peaks and decreasing it.

1 So the current methodology is feasible
2 within the practical limits of the sampling and
3 turn around time.

4 Now of course if you had a dip stick
5 methodology and a color code that said high, you
6 could use something like that to increase your
7 sampling, even to within a day. I mean, you
8 know, if it really was moving fast, you could be
9 picking samples hourly.

10 Dr. Heeringa?

11 CHAIR HEERINGA: Steve Heeringa. Just
12 to be clear, when I was talking about being
13 adaptive, I was thinking the feedback might be
14 annual. But as usual, Dr. Portier has a shorter
15 cycle on these things than I do.

16 SESSION CHAIR PORTIER: So you are
17 talking about using last year's profile to tell -
18 - The unfortunate problem with that, of course,
19 is climate.

20 So you know, a lot of this does seem
21 to have a relationship to rainfall. And so while
22 there is a persistence in climate, it is not

1 strong enough that you can really use that.

2 CHAIR HEERINGA: But I would say that
3 there are multiple variables in this work model,
4 including how much crops planted, the absorption
5 of the system, flux through the system. That
6 probably has more temporal permanence than the
7 climate. We are not going to predict the
8 rainfall but we can predict roughly when people
9 are going to plant crops, when the atrazine is
10 going to go on the field and roughly how systems
11 are going to respond in the cross different
12 rainfall events.

13 So I think we are averaging over and
14 we don't want to over adapt. But I am just
15 saying that if you were in a system that clearly
16 showed much more variability than the sort of
17 averages on which you are basing your sampling
18 plans, then there might be an argument over time
19 to intensify sampling for that system, until you
20 were confident that you were getting what you
21 wanted for that system.

22 SESSION CHAIR PORTIER: This is Ken

1 Portier. And I think we are only repeating
2 recommendations we made at the SAP a year ago
3 when we looked at the ecological issues related
4 to environmental sampling. So you can go read
5 those.

6 Dr. Gilliom.

7 DR. GILLIOM: Just, one comment here
8 since it is not really brought up in the charge
9 questions later, and it is on this issue of
10 whether there is some short-term adaptive
11 approaches that could be taken. And I don't
12 think it is worth getting heavily into this at
13 this point.

14 But if it was to turn out that there
15 is a really short term concentration objective
16 that is extreme, like a one or two-day type of
17 thing, then it really would be possible to use a
18 quick screening process, like an amino assay test
19 for atrazine triazines and just do it in the
20 water plant and make decisions.

21 So there are tools. They can trigger
22 a laboratory analysis and they are well-known and

1 well-characterized. So if that becomes a big
2 issue, I think it is a discussion item that
3 should be thought through.

4 SESSION CHAIR PORTIER: Make sure you
5 add that to the report.

6 Okay, I think we have stretched this
7 one out as long as we can. Why don't we move to
8 question 2.2?

9 MR. THURMAN: I would be glad to. The
10 first two simulation methods presented in Section
11 5.5 are applicable to the specific data sets they
12 describe, although some generalities regarding
13 shape patterns appear to exist. Given this
14 information, please comment on the strengths and
15 weaknesses of the approaches and on the practical
16 merits of pursuing them or some other numerical
17 approach with a larger set of higher
18 concentration systems. Please comment on how the
19 methods for determining confidence bounds might
20 apply given these considerations.

21 SESSION CHAIR PORTIER: Dr. Gilliom.

22 DR. GILLIOM: Okay so some of this has

1 been talked about a lot. So I am going to kind
2 of abstract from my comments.

3 Both the methods that are referred to
4 in here follow the same concept we have talked
5 about this morning. And generally it is the
6 concept described in the Crawford paper 2004 in
7 which the actual data for selected sites are
8 interpolated between samples, and then treated as
9 truth, and then sampling experiments are done
10 from them.

11 So I think as I said before, probably
12 my comment would sum up that the approach makes
13 sense if the initial actual data are sufficient
14 to simulate reality for the problem at hand.

15 And so in this specific example, just
16 to pick on the two ones that are in here as
17 examples, is that they are not, they are examples
18 of simulated truth from real data that are not
19 adequate to address a short-term concentration
20 objective. So these were examples generated from
21 30 to 40 samples a year and then they were
22 interpolated to create a simulated truth, and

1 then they were subsampled to test how they did
2 for doing shorter term concentrations. It is
3 like a seven-day or four-day average or whatever.

4 So and I think everybody realizes that
5 but they are actually good examples of what to
6 watch out for. The analytical process is fine
7 but the specific application is not appropriate
8 for short-term.

9 And so I think the general point I
10 would leave it with is that yes, the basic
11 approach is good. We have to make sure that once
12 the concentration objectives are defined very
13 precisely and probably more precisely than
14 anybody is going to feel comfortable with on the
15 biology end but the Agency is still going to have
16 to do it is that then we design a sampling
17 analysis process that fits that.

18 And I think I will just leave that
19 there.

20 SESSION CHAIR PORTIER: Dr. Coupe?

21 DR. COUPE: I don't think I have too
22 much to offer to Dr. Gilliom. I just say there

1 isn't a great method for extrapolating these
2 data. You have what you have and if you need to
3 find a resolution then you just need to collect
4 more, collect measurements.

5 SESSION CHAIR PORTIER: Dr. Lee?

6 DR. LEE: I don't think I really have
7 anything to add to this one. I will have more to
8 say probably later about modeling and bringing it
9 in but I will hold that to number four.

10 SESSION CHAIR PORTIER: Dr. Young?

11 DR. YOUNG: This is one that probably
12 from your view, unfortunately, I feel strongly
13 about.

14 The real question that is not answered
15 that really has to be answered before we know how
16 to simulate is how important are the peaks and
17 how long do the peaks last? And we don't really
18 have that information right now. But there is
19 one thing that I think needs to be made really
20 clear and I think we have hit around it several
21 times but it so important I want to hit it again.

22 If one wants to draw inference at the

1 daily level, based solely on the data collected,
2 sampling must occur at least daily. If one wants
3 four-day rolling averages, you can't have a
4 rolling average without a least two values. So
5 the minimum would be two in those four days and
6 that may not be enough.

7 Simulations, models or any other
8 approach that suggests otherwise is making some
9 strong assumptions about what happens at the
10 finer timescale.

11 Now, if a good understanding of the
12 systems exists, then one may be able to model the
13 results, in which case sampling could be
14 confirmatory. But this requires knowledge of the
15 system and sufficient supporting data to
16 construct such a model for each side, something
17 that is not present here, at least not yet.

18 It does seem to be reasonable to
19 concentrate sampling effort during the time of
20 exposure. However, as Bob has noted several
21 times, the sampling scheme developed for atrazine
22 may not be applicable to other contaminants.

1 The thing that bothers me about all
2 the simulations that we have seen here is that
3 they are smooth versions of reality and that is
4 true even for the daily data that we have. There
5 is no accounting for measurement error,
6 variability within the day, or all the other
7 things that happen when you are out in the field.
8 And anyone who has been there knows how bad that
9 can be.

10 It would seem to me that a more
11 reasonable approach for simulations is to try to
12 bring some modeling information such as the WARP
13 to generate chemographs with typical behavior and
14 then to bring the variability associated with
15 that modeling process to bare. So you would have
16 a realization of the chemograph followed by an
17 analysis in that realizations would be replicated
18 so you would capture all of the variability in
19 the system. You wouldn't just be hinging on one
20 particular realization of the chemograph.
21 Because even if it is real, it is dead and gone.

22 That is not about what is happening in

1 the future and I think we need to capture that
2 variability in the simulations because I think as
3 a consequence of doing it the way we have been
4 doing it, it makes everything look better than it
5 should and that is a little scary.

6 So that is, I think, the primary point
7 I want to make.

8 SESSION CHAIR PORTIER: Additional
9 comments?

10 This is Ken Portier. When I looked at
11 this, you know, to me the strength of the
12 methodology as Linda mentioned in the first
13 question is that is its non-parametric nature.
14 So a lot of it you are going kind of back to
15 first principles of sampling. You are
16 simulating. So to me, that is the strength of the
17 process.

18 The weakness is the starting data. It
19 is clear. You know, if the starting data is an
20 inadequate representation of what is really
21 happening that the water system, nothing that we
22 can do statistically is going to improve that

1 starting data with any kind of first principle
2 statistical methodology. You are going to have
3 to go to modeling or more sampling. I mean, it
4 is kind of that simple.

5 Now, I personally like the WARP
6 approach because I know that there is other data
7 out there, climate data, soil data, that is
8 sampled even more regularly than these water
9 system data is sampled. And so through modeling
10 we can use the correlation relationship and be
11 able to impute a little more of what is going on.

12 And so I do like that kind of approach
13 because it just uses more data, uses the
14 information. And that includes kind of modeling
15 from the well water to the water that comes out
16 of the community water system. I haven't seen
17 any modeling talking about the effectiveness or
18 the methodology.

19 I mean, you talk about activated
20 carbon systems but do those fail when the
21 concentrations reach a certain level. I mean,
22 you know, some of these systems work well when

1 there is just a little bit coming in. But then
2 if the ability of the carbon to capture these
3 molecules gets overwhelmed by the concentration,
4 you could actually have a discontinuous peak kind
5 of event happening as well. So I think you need
6 that kind of. And that is probably a whole other
7 division in EPA that you have to go and talk to.
8 Right?

9 Mr. Thurman?

10 MR. THURMAN: I do want to point out
11 on the drinking water treatment, we have actually
12 came to the SAP a number of years ago on drinking
13 water treatment and what we knew, what the state
14 of the published literature was on that. We have
15 continued to keep an eye out on that and update
16 that to the extent we do.

17 Generally when we are doing drinking
18 water exposure assessments that would be used in
19 dietary exposures, we addressed drinking water
20 treatment effects as separate at another end of
21 the process. So we didn't bring this to you
22 because we addressed them separately but it is a

1 point well taken.

2 In fact, I looked at it, and you are
3 starting to look at sources of variability. You
4 throw in the drinking water treatments, you start
5 to expand your sources of variability that you
6 have to address. So we were trying to take a
7 simpler approach then we can layer that on. But
8 that is a point we will.

9 SESSION CHAIR PORTIER: I mean, I
10 recognize as a public health risk assessment
11 methodology, you can put limits on raw water
12 because as long as you can argue through that raw
13 water back to a consumption and a risk.

14 So I mean I recognize that as long as
15 you have kind of got that continuum explained, we
16 can still go back and say well but we don't want
17 to see any input, raw waters above a certain
18 level because we know that gets translated for
19 all these processes, with all these uncertainties
20 into levels that are not safe. So, you know, it
21 is just that, and you guys know.

22 Any additional comments? Dr. Gilliom.

1 DR. GILLIOM: Just to add to the
2 thought on the model application. I think we are
3 in a position to very effectively use the
4 available models built from existing data to
5 identify with known probability the sites that
6 need the attention for a specific objective.

7 So there is a lot of points in there
8 to follow but once the objective is defined we
9 can, in other words, estimate which specific
10 sites. And then I think we have to remember in
11 evaluating all these methods, that and it is the
12 agency's direction, I think appropriately, that
13 once you are to that point, each individual
14 system on its own becomes the focus, not some
15 aggregate statistics for that group or anything.
16 It is that system and those people that use that
17 system.

18 And at that point, the problem can be
19 further evaluated as needed, including adaptive
20 sampling or in some cases as brought up in
21 examples, differences between the intake screen
22 water, holding reservoirs and finished water.

1 Because at this point, you are down to a very
2 small proportion of the community water supplies.

3 So it is a part of an overall
4 decision-making process that right now we are
5 only talking about the FIFRA add-on, that is what
6 I call it anyway, to regular compliance
7 monitoring. We haven't even, I mean, a
8 compliance monitoring is not involved yet. It is
9 still over there on quarterly sampling per year
10 but it could eventually be affected by this down
11 the road if the Office of Water chooses to do
12 that.

13 SESSION CHAIR PORTIER: Okay, I don't
14 see any additional questions. I think you got a
15 pretty good answer on that one.

16 MR. THURMAN: I think we got an
17 answer.

18 SESSION CHAIR PORTIER: Let's move to
19 2.3.

20 MR. THURMAN: As described in Section
21 5.4.2 of the issue paper, the Agency is
22 considering the use of a confidence interval or

1 prediction interval approach to characterize the
2 uncertainty of exposure estimates derived from
3 monitoring data of varying sampling frequencies.
4 Please comment on the strengths and weaknesses of
5 either placing confidence bounds on the rolling
6 average estimates and comparing to the upper
7 limit from monitoring against the level of
8 concern or, conversely, placing confidence bounds
9 on the LOC.

10 And I apologize. That was written by
11 committee. I hope you will be glad to clarify
12 that.

13 SESSION CHAIR PORTIER: Dr. Coupe, you
14 are first up. It looks like there were four
15 people assigned to these four questions and then
16 Joe used the random number generator to assign
17 who was first.

18 DR. COUPE: When I saw the list of
19 questions come out without names attached, I
20 looked at 2.3 and said, "Dear God, I hope I don't
21 get that one."

22 (Laughter.)

1 DR. COUPE: I think I understand the
2 second part of this. And I will paraphrase and
3 you correct me if I am wrong but you are talking
4 about in the second part of taking the
5 uncertainty in creating an LOC and then creating
6 a bound around that and then testing your data
7 against that.

8 MR. THURMAN: That is correct.

9 DR. COUPE: So, I just leave the
10 particulars of the statistics details to my
11 colleagues doing a 95 percent confidence interval
12 slapped over another 95 percent confidence
13 interval. But I don't really think you want to
14 do that, just given the variability of how an LOC
15 is derived and the different safety factors and
16 moving from animals to humans. I think you
17 probably wanted to stick with the LOC number.

18 But I am going to move into a little
19 more broader thing. I am talking about the
20 variability of using a statistical method to
21 determine future sampling scenarios. I know we
22 had to do that. But it assumes that the

1 distribution, the constituent of instrument is
2 going to be the same from year to year and we
3 know it is really not true.

4 There are many things that change from
5 year to year that might change, that change the
6 distribution of atrazine in the surface water of
7 our basin. So when we talk about year to year
8 variation in rainfall as well as long-term
9 climate change, the changes in crop types, for
10 example, you get a new cold weather variety that
11 can be planted earlier or later.

12 We have a lot money going into the
13 Mississippi River Basin now for BMPs and these
14 have the ability to change how the atrazine is
15 moved into the surface water. And you are going
16 to have changes in the weed population and the
17 weed infestation which have changed your
18 herbicide use.

19 But I just wanted to give you a little
20 brief recap of herbicides in water, just kind of
21 a 101 on the distribution of atrazine in surface
22 water. The distribution of atrazine in surface

1 water can really be explained in two terms, a
2 source strength and a hydrology. A source
3 strength being the fact that for atrazine to be
4 detected in the surface water of a basin, it has
5 to be used in that basin. We have mentioned work
6 before but if you look in WARP, the single
7 largest parameter that explains variability and
8 explains more variability than all the rest of
9 the parameters combined was use. So, was
10 atrazine used in the basin? If it was, then some
11 small proportion of the applied amount ended up
12 in surface water.

13 And the other important factor in the
14 transport of atrazine is water. There must be
15 water to move atrazine into the stream of the
16 basin. For the most part, atrazine is also
17 transported atmospherically but the
18 concentrations here are moved off the landscape
19 by water.

20 So the EPA has stated how hard it is
21 to relate concentrations to the streams of flow
22 and I agree that it is because the concentration

1 is made extremely high with a very small runoff
2 event soon after application and there may be a
3 very small concentration, a large runoff event a
4 few weeks later. But I submit that hydrology can
5 explain the presence or absence of atrazine in
6 streams.

7 Additionally in larger streams, the
8 variability of concentration may be due to the
9 timing of the arrival of water at the intakes
10 from various parts of the basin. Some may be
11 having more rainfall than others. Or maybe
12 planning was further along in one area of the
13 basin than it was in another one.

14 There is an awful lot of information
15 and expertise on the transport of agricultural
16 chemicals and I am convinced, as opposed to
17 determining if, atrazine poses a health risk. It
18 is not rocket science. A program can be designed
19 that will do what is needed to do if we know what
20 is needed. What you need to know and have to
21 know to design a program is what is being
22 discussed here as what is the endpoint. At what

1 level does the atrazine concentration in water
2 matter to humans or the environment? It makes a
3 big difference if it is 25 ppb or 0.25 ppb.

4 That being said, here is a few more
5 random comments. I don't think a one size fits
6 all approach is necessary. Crawford showed in
7 his paper that the larger the basins, the less
8 data you need to reach precision goals.
9 Conversely, of course, the smaller the basin, the
10 flashier it is and the more samples are needed to
11 ensure precision. Given that there is
12 significant history at these sites and many have
13 shown only small levels of atrazine, I believe
14 the sampling strategy could be tailored for
15 individual community water systems, probably less
16 samples on the larger systems and maybe more on
17 the smaller ones.

18 And earlier, there was a discussion
19 about daily sampling. I just want to iterate
20 that as my colleague Linda put it. If you need
21 fine resolution, and she said it several times
22 already, then you have to sample at a fine

1 resolution. If you want a four-day average, I
2 thought it was a very good point, a four-day
3 average, you have to sample twice. Yes, you
4 can't really create, interpolate or model data if
5 that is what you need. I whole heartedly agree
6 with that and that goes for even sub-daily
7 sampling, which we haven't even mentioned about
8 because some of these basins may have variability
9 that relies on the sub-daily.

10 So and also just one last point as we
11 mentioned before. I would like to point out that
12 although there is a lot of very good work on the
13 toxicity of atrazine, from my own experience and
14 as the woman from NRDC stated, you never find
15 atrazine alone in a water sample. There is
16 usually a plethora of other constituents, some
17 herbicides, other kinds of materials that are in
18 there. You just never find atrazine alone.

19 So to study the toxicity of atrazine
20 alone kind of short-sheets safety. I think it is
21 a serious concern. Thank you.

22 SESSION CHAIR PORTIER: Dr. Gilliom?

1 DR. GILLIOM: I guess on the response
2 to that specific question, you know, my tendency
3 is to not try to put additional, this is an
4 agreement with Dr. Coupe, try to put confidence
5 bounds on the LOC. It seems by its nature it is
6 a process of putting in safety factors and coming
7 up with a conservative threshold. So at least
8 once that is all done, you do have a fixed value
9 to compare something to. I don't think we should
10 start trying to do even more with that.

11 I do think it is really important that
12 we have agreed upon and predictable ways that
13 confidence bounds are going to be put on the
14 exposure estimates. And part of the reason I say
15 that is that I think in the end we are going to
16 have a whole continuum of approaches being used
17 to estimate exposure. So you could envision
18 potentially a high probability group of sites
19 that you have very dense actual measurements on
20 and very tight estimates of confidence on one
21 hand. And those are going to have a different
22 probability of exceedance issue than if we are

1 using an indirect method from a model, which is
2 also going to be an important part of the
3 continuum.

4 So I would kind of view it in terms of
5 we would like to see, I would like to see the
6 objectives stated in terms of acceptable
7 probability of exceeding a given threshold. That
8 way, we can look at any method on a common
9 playing field. So in other words, if the EPA
10 gives us guidance and says okay, the moving
11 average value is seven, seven-day value of 20,
12 and it is okay with us that there is a 50 percent
13 chance that that is exceeded, then we can look at
14 any estimation method on a common basis and
15 evaluate the probability on those terms. And
16 that is not easy to do but in the end, that is
17 what it kind of comes down to, even if you have a
18 very shallow basis for estimating the numbers.

19 SESSION CHAIR PORTIER: Dr. Lee?

20 DR. LEE: Yes, I concur with my
21 colleagues here. And I just want to say that
22 statistically the problem of placing confidence

1 bounds on a level of concern is a harder problem
2 than just putting confidence bounds on a rolling
3 average. And there is going to be enough
4 complication perhaps in other things that we want
5 to do with this, that this may not be the place
6 to add additional complication.

7 SESSION CHAIR PORTIER: Dr. Young?

8 DR. YOUNG: I have nothing to add.

9 SESSION CHAIR PORTIER: That just
10 increased my probability of getting through this
11 morning. Anyone else?

12 Yes, I tended to concur also. I mean
13 I thought about this and I thought to myself
14 exactly as you say, it is probably a lot harder
15 to put a confidence interval in a limit of
16 concern and it leads to more public confusion.
17 The exposure estimate, everybody assumes exposure
18 is going to be variable so a probability
19 statement on exposure is probably much more
20 acceptable than one on a public health limit of
21 concern. So I think you have got a pretty clear
22 answer to this question. It kind of gives you

1 the direction.

2 MR. THURMAN: Yes, we appreciate that.
3 Okay, so question 2.4. We just scared Don off.

4 SESSION CHAIR PORTIER: He had warned
5 us that he had to leave for another meeting.

6 MR. THURMAN: I am just picking on
7 him. I will pay for that later.

8 SESSION CHAIR PORTIER: We won't see
9 him again. Right?

10 MR. THURMAN: Well he has got six
11 months to forget about that.

12 Okay, this is, it looks like a two-
13 part question. I will read them both and you can
14 -- three part. Oh, gosh. Okay. I apologize in
15 advance for that.

16 Please comment on the relative merits
17 of the various modeling approaches the Agency
18 described in Sections 5.4.1 and 5.6 for
19 interpolating pesticide concentration between
20 sampling points and, in particular, on the
21 strengths and weaknesses of these methods as the
22 frequency of samples decreases.

1 Considering the health endpoints being
2 considered for atrazine, particularly data for
3 the HPA axis, and the exposure time frame needed
4 to induce the health effects, which is shorter
5 than that used in the 2003 risk assessment,
6 please comment on the advantages and
7 disadvantages of each model for evaluating the
8 likely occurrence and exposure via drinking water
9 of short, moderate, and long durations.

10 Please comment on the Agency's
11 proposed approach for evaluating these methods,
12 as described in Section 5.7.1. To what extent
13 should the Agency consider other factors, such as
14 the shape of the chemograph(Section 5.5.3),
15 weather patterns, stream flow, and/or pesticide
16 use patterns in evaluating the modeling
17 approaches?

18 SESSION CHAIR PORTIER: Dr. Lee?

19 DR. LEE: You gave me the long one.

20 All right. Let's charge in.

21 Section 5.4.1 describes two basic
22 methods for filling in values between the actual

1 measurements one-year interpolation, stair-step
2 imputation. Neither of these methods can ever
3 give you a predicted value that is larger than
4 any of the observed values. So this clearly will
5 lead to underestimation of the maximum value, if
6 the maximum value does not occur on a sampling
7 day. And this carries over then into shorter
8 term averages or any average as well. The
9 shorter the average, the more important this peak
10 is.

11 The stair-step method has, I think,
12 further danger of missing the truth here. In
13 terms of following the curves, you are trying to
14 get an average, the stair-step method will tend
15 to overestimate a decrease in curve when it is
16 concave -- will tend to overestimate a decrease
17 in curve. Linear interpolation also will tend to
18 overestimate if the decrease is concave but by
19 not as much as the stair-step method.

20 From the examples of chemograms that
21 were given in Figure 7, I get the impression that
22 most curves generally will be concave from more

1 of the year then convex because there is an
2 initial peak following the application of the
3 pesticide, followed by proportional decrease from
4 the peak. And maybe my hydrologist colleagues
5 can correct me on that but that is the impression
6 I get of these shapes.

7 So among these two methods, the linear
8 interpolation does seem like it is probably going
9 to do a little bit better. But for the most
10 part, it probably doesn't matter. We are missing
11 the maximum significantly. There is the
12 potential for missing the maximum significantly
13 here.

14 For longer term averages, like a 90
15 day average or 26 week average, both the linear
16 interpolation stair-step methods seem to work
17 reasonably well because the underestimation of
18 the peak values can be balanced by overestimation
19 of post-peak values. It is not exactly a ringing
20 endorsement but central limit theorems kicking in
21 for us there.

22 But to accurately estimate a maximum

1 value when it is out of sample, it is going to
2 require use of a method that can predict a larger
3 value than those that are observed in the data.
4 And example of such method is an artificial
5 neural network as described in 5.6 and Appendix
6 C.

7 Let me just briefly mention again what
8 I brought up on, I guess it was Monday. Appendix
9 C does describe the importance of not using too
10 many nodes because over-fitting is not good for
11 prediction. Absolutely correct. But if you are
12 using too few nodes, then you will also
13 potentially be not fitting the curve very well.
14 The shape of the peak may not be correctly
15 categorized and you may be missing the maximum
16 value as was shown in the difference between the
17 three-node fits and the four-node fits in the
18 White Paper.

19 So the importance of finding the right
20 number of nodes is critical for getting good
21 estimates and some sort of basic model selection
22 like a BIC measure would be helpful. That may

1 also be able to eliminate the need for fitting
2 autoregressive errors. I think the current
3 approach that involves the neural network with
4 autoregressive errors is just going to be too
5 complicated for a non-expert to implement and
6 thus, it is not necessarily a practical approach
7 but perhaps if we can eliminate the need for
8 autoregressive errors, it may become a more
9 useful approach in this context.

10 Section 5.4.1 also mentions a number
11 of other potential approaches: bootstrapping,
12 kriging, random function models, regression-based
13 models and deterministic models. Bootstrapping
14 methods again are never going to be able to
15 predict a value that is larger than you actually
16 observed. So, that leads to definite worries.
17 The other four methods do have promise alone or
18 particularly in combination.

19 Kriging, which is the basic case of
20 fitting a Gaussian process model interpolates the
21 data with a smooth curve but does allow the curve
22 to move outside the bounds of the data. And so

1 it could be used for estimating a maximum that
2 occurs outside of the sample base.

3 Also like a Gaussian process, like a
4 neural network can be used to smooth noisy data,
5 rather than doing strict interpolation. That is
6 an issue that I don't think has been discussed
7 here. The Agency uses interpolation a lot in the
8 White Paper but there is a difference between
9 strict interpolation which necessarily will go
10 through all the observed points and some sort of
11 curve fitting, which may discount exact values
12 because of say measurement error. And so the
13 curve will get close to the points but it will do
14 some smoothing. The neural network approach is
15 an example of smoothing approach. It is not
16 guaranteed to go through all the data points and
17 we wouldn't necessarily want it to go through all
18 the data points. But the interpolation methods,
19 the linear interpolation stair-step are, by
20 definition, interpolation. They are guaranteed
21 to go through the data points. Kriging, in its
22 basic form is an interpolation method. It will

1 go through all the data points but
2 generalizations to Gaussian processes allow more
3 flexibility if that is not necessarily the case.

4 Let's see. I did actually get some
5 examples of the community water system data from
6 Marry Frankenberg and was able to fit some basic
7 kriging models to them and found that well, it
8 doesn't actually do a whole lot better than
9 linear interpolation in most cases. In most
10 cases, I was not able to get a fit that gave me
11 maximum values outside the sampling days that
12 were higher than the observed ones.

13 And my guess just from really basic,
14 you know, I didn't have a whole lot of time to do
15 the analysis in the last two days, my guess is
16 that the shape of the peaks are very sharp. And
17 as such, the correlation structure is somewhat
18 different around the maximum than it is in the
19 rest of the space. And so fitting a standard
20 stationary model as kriging would do, is not
21 adequately characterizing the curve. A more full
22 analysis would involve a non-stationary

1 correlation model and these do exist. But again,
2 I think this is going to be far more complicated
3 than you would want to implement on an individual
4 community water system out in the field.

5 One last issue around kriging is that
6 you do need to estimate a correlation structure.
7 These are difficult to estimate. Empirical
8 chemograms are highly variable and so I would
9 recommend the estimation be done more globally,
10 pooling across years and across water systems.
11 Okay, that is kriging.

12 Random function models are another
13 approach we can use. Essentially there we are
14 picking a shape for the curve. And we do know a
15 fair amount about what these curves may look
16 like, although they differ from system to system.
17 Using those shapes can really aid in the
18 determination of a maximum value and can help
19 them say in determining if the maximum value may
20 have occurred on a sampling day or a non-sampling
21 day. And if it is a non-sampling day, be able to
22 estimate how much higher is that peak.

1 And there are a number of ways to do
2 this. There is an example in the context of
3 pesticide concentrations given by Vecchia et al.
4 in a 2008 paper, essentially Dr. Gilliom is on
5 that one, essentially using the WARP model to
6 look at predicting -- it is combining the work
7 model with seasonal shaped functions to be able
8 to make predictions about where that peak might
9 be.

10 So that ties into regression-based
11 models. And there has been a number of work by
12 Dr. Gilliom and others at looking at regressions
13 to predict maxima and quantiles and there is a
14 lot of potential there. They do, however, are
15 looking at sort of the yearly total. So just
16 looking at the maxima over the whole year, it is
17 not going to give you a time series on its own
18 there. And the accuracy may not be quite at the
19 level that one would want for an individual water
20 system but I think there is a lot of potential
21 there. In particular, there is a lot of
22 potential for combining these regression-based

1 models with other sorts of models to get improved
2 information and help us make out-of-sample
3 predictions.

4 The final method is used, the final
5 method mentioned in the White Paper is
6 deterministic models. These are built from a
7 combination knowledge of the physical and
8 chemical laws of the process, looking at the
9 actual physical process. And those can be really
10 useful for predicting maxima and short-term
11 averages when we don't observe the data directly.

12 But an important issue there is
13 calibration, which involves the setting of inputs
14 and possible tuning parameters so that the
15 predictions do closely match observed values.
16 And there is the concern that this may need to be
17 done for each watershed individually and then
18 that becomes a complicated problem again.

19 I guess one global theme here is you
20 don't get something for nothing. If you want to
21 be able to make predictions in-between the
22 observed days that are more accurate, it takes

1 more work.

2 I do want to mention one other
3 category of models that has not been mentioned in
4 the White Paper and that is using extreme value
5 theory. There is a fair amount of theory in the
6 statistics literature about modeling extreme
7 events and their distributions developed around
8 those. And I think Dr. Young has mentioned some
9 of these earlier. But there are some, and there
10 is some very recent work. There is a paper that
11 just came out in the Journal of the American
12 Statistical Association that looks at methods for
13 modeling extreme values of a correlated process.
14 Most of the literature involves independent
15 samples but some of the more recent work does
16 look at correlated processes such as chemograph.
17 And so that could be really useful to be looking
18 at. It is a very new literature and I am not
19 that familiar with it but I think the EPA should
20 at least investigate that literature.

21 MR. THURMAN: If you could put that in
22 your report --

1 DR. LEE: I will put all the
2 references --

3 MR. THURMAN: -- that would be great.

4 DR. LEE: -- in the minutes.
5 Absolutely.

6 Okay, so I think that gets through
7 parts one and two of this question. Part three
8 then is about the procedure for evaluating the
9 effectiveness of the different methods given in
10 Section 5.7.1. And the general approach I think
11 is sound but as mentioned before, it is important
12 to make sure that we are using a truth that is
13 realistic and so has enough level of detail and
14 variability that reflects what we will actually
15 see.

16 And then the important point is the
17 last part of the question asks about other
18 factors. And I think those really, really should
19 be looked at, taking into account possible
20 covariates, like weather patterns, stream flow,
21 pesticide use patterns, would really help in
22 being able to make better estimation or also the

1 shape of the chemograph.

2 So combining these sorts of other
3 pieces of information would really help. Trying
4 to estimate the maximum, just looking at the data
5 non-parametrically, we can do that but it is not
6 as powerful as bringing in other information that
7 we do have available.

8 And again, Dr. Gilliom has been
9 involved in some work that relates those pieces
10 of information and I think that would be a
11 critical direction for the agency to further
12 investigate.

13 SESSION CHAIR PORTIER: Thank you.
14 Dr. Coupe?

15 DR. COUPE: I think anything I wanted
16 to say I have already said. And that was pretty
17 comprehensive. So that is it for now.

18 SESSION CHAIR PORTIER: Dr. Gilliom?

19 DR. GILLIOM: Just I guess one thing
20 to make clear is between Dr. Lee and myself, we
21 will make sure all the references are in there
22 for the various articles. They will be included

1 in the write-ups.

2 One, I guess point I want to make is
3 that if the, and it is probably just a repeated
4 implication of the discussion here but if the
5 duration is on the very short end, it is going to
6 be evident pretty quick, I think that we don't
7 have enough range of conditions covered of
8 existing examples of intensively monitored sites.
9 So we have a few sites from Heidelberg College.
10 We have got a couple of drinking water sites. It
11 is growing but we don't really have the full
12 geographic range of conditions represented. So
13 there will be some important decisions to make
14 there about what that means about how far we use
15 inference from existing data. But there is no
16 point in addressing that or even trying, I think,
17 until we know the concentration objective from
18 the toxicology side from the Agency.

19 And I think that is enough to add for
20 now. Thank you.

21 SESSION CHAIR PORTIER: Dr. Young?

22 DR. YOUNG: I also thought Dr. Lee did

1 a nice job in summarizing. One of the things
2 that kind of pull some ideas that have already
3 been stated that maybe pulling them together is
4 that it seems to me it makes really good sense to
5 use the WARP or some other model to identify the
6 most vulnerable community water systems.

7 And then once you found those, then it
8 is probably worth some time and effort to figure
9 out exactly what should be done for those
10 systems. And the methods that have been
11 proposed, interpolation methods, might work fine
12 as long as a 90-day rolling average is fine. But
13 if we begin shortening them up, they are not
14 going to be sufficient.

15 So some way to get a more realistic
16 chemograph is important and that would seem to
17 call for maybe the simplest I can think of is a
18 regression-type model where you put in some
19 kriging and then once you have that, you can use
20 geostatistical simulation to get an idea of the
21 true variability associated with that and maybe
22 begin putting some bounds. And then you have a

1 fairly good idea of what might happen within that
2 system.

3 Now that would take more time but if
4 we narrow the scope of the systems, then perhaps
5 you have more time for individual efforts. And
6 then once you get -- the first one always takes
7 the longest. So that is something to think
8 about.

9 SESSION CHAIR PORTIER: Any additional
10 comments from the panel?

11 One of the things I thought about, we
12 haven't really talked too much about the rolling
13 average methodology. But you are using a fairly
14 simple approach of just taking a couple of points
15 and doing the regular average. And there is a
16 slight improvement you can do on that, which
17 would be more of a weighted average. I was
18 thinking Linda, isn't it more like a lasso-type
19 approach that still gives you a good average?
20 But you notice on the graphs that Mr. Thurman
21 showed that with the rolling averages, their
22 average profile is always going to be shifted to

1 the right of the real profile and that is a
2 function of just doing a simple average, rather
3 than having a slightly wider window with some
4 weights, some decreasing weights on either side.

5 So there is kind of a weighted
6 smoothing that will give you kind of a similar
7 rolling average but one that kind of matches up
8 in terms of its peaks and its valleys with more
9 of the original profile.

10 The other thing I was thinking of, a
11 comment Dr. Gilliom mentioned about, more
12 intensive sampling from more sites, is that it
13 would be nice to have some "normal sites." The
14 interquartile range sites. You know, to sort of
15 ensure the public that we haven't just looked at
16 worst-case scenarios. We have also looked at
17 some good players, some solid citizens in the
18 middle. CWS's that don't have all these major
19 problems that are overall managed, that our
20 methodology works well in those kind of solid
21 citizen sites as well. You always aren't always
22 in the extreme because you get charged with being

1 too extreme at that point. Right? And not
2 really giving us a good picture.

3 And as far as the White Paper, you
4 know, when you looked at the neuro network and
5 showed us how well the smooth to the neuro
6 network worked and then you added in the
7 autoregressive two component, you didn't show
8 really how well that improved that process. And
9 the point that Dr. Lee was making on some other
10 models is that kind of adding is nice
11 statistically and it may improve the R-square
12 three percent but when you looked at the picture
13 of the smooth, it probably isn't something that
14 is really noticeable. And so if you are looking
15 to simplify, statistically that is nice but in
16 terms of complexity, it really adds a lot of
17 complexity to the estimating process to be able
18 to do that. That may not pay off in the long-
19 run.

20 I think that is the end of my
21 comments. Dr. Heeringa.

22 CHAIR HEERINGA: Just one minor

1 statistical observation, too, which I think
2 people probably recognize but we didn't mention
3 and that is in the sampling process itself,
4 regardless of the periodicity with which you draw
5 single samples, the sort of every nth day
6 sampling, systematic sampling would be most
7 efficient if you had sort of long-term monotonic
8 trends, increases or decreases. But if you have
9 arbitrary fluctuations on shorter terms, that
10 systematic sampling may actually give you greater
11 variance than something that is more randomly
12 perturbed within the fixed windows.

13 And I think that between what RTI did
14 and Syngenta and what Dr. Sielken did and what
15 you have done in your simulations, you might
16 actually be able to see that one some
17 chemographs. I don't know if it has been
18 structured that way but you could actually test
19 that.

20 But it is just a small point but I
21 think systematic sampling is great if you are on
22 a monotonic trend but could in any given sample

1 lead to greater variance or error than a randomly
2 perturbed sort of fixed window sample. It is
3 just a minor issue but is probably something
4 technically not to lose track of in the process.

5 SESSION CHAIR PORTIER: Yes, Dr.
6 Gilliom?

7 DR. GILLIOM: Just a tangent that
8 reminded me of, that it is maybe important to how
9 we translate ultimately the monitoring
10 requirements from the toxicological requirements
11 is just to remember that all of the data we are
12 looking at so far and what is normally done are
13 instantaneous grab samples for the most part.
14 There is a few data sets that have auto samplers
15 that are doing composites either flow or time
16 waved and so forth.

17 But if it is an important thing to
18 capture for instance to know that we have a time-
19 weighted daily value or a time-weighted two-day
20 or three-day value, that is important information
21 to have in the LOC. Because too often, that type
22 of information is left out and then the

1 monitoring design goes ahead with variants based
2 on instantaneous samples and all that and it may
3 not capture what you really want it to for the
4 biological effects. So I think we can deal with
5 all that, the Agency can deal with all that but
6 we need to know the specific objective from the
7 biological point of view.

8 SESSION CHAIR PORTIER: I am sitting
9 here thinking we need a synthetic drinker that
10 drinks two liters of water out of it in a day and
11 then composites that and gets an average
12 concentration. That's okay.

13 Any additional comments?

14 So that, I think is the last question.

15 MR. THURMAN: Mercifully so.

16 SESSION CHAIR PORTIER: And before I
17 close, we usually do two things, and one is I am
18 going to open it up to the panel for any final
19 comments from any panel member. If there is some
20 topic you felt that hasn't been brought up that
21 you wish to comment on, we can add this in at
22 this point. I think we pretty intensively

1 covered a lot of these topics but we will open it
2 up to anyone.

3 Last chance to say anything before I
4 turn it over to EPA for their closing remarks. I
5 don't see anybody dying to present a new issue.
6 Dr. Lowit, I know she has a few closing comments.

7 DR. LOWIT: Before I speak on behalf
8 of the team to give you our appreciation and our
9 sort of next, what we will be doing now, I will
10 speak on behalf of myself.

11 A little story. A number of years
12 ago, probably eight maybe nine at this point, I
13 had only been with the Agency a year or so, two
14 years at the most and it was the night before the
15 first big meeting I ever gave a big presentation.
16 A group of us were meeting with the office
17 director at the time. It was several office
18 directors ago. This person was going around the
19 table giving a little pep talk and it came to my
20 turn for a little pep talk. And the comment that
21 I was given was you will do great. Just don't be
22 flip. And I will forever hold that.

1 And yesterday I think I said a couple
2 of things that were flip, unfortunately. And I
3 always think of that day because it absolutely
4 nailed my shortcomings. But I did, I think, make
5 a comment that could have, around the science
6 issues that was probably interpreted by all 20 of
7 you 20 different ways and I just want to take a
8 second and clarify something that I said.

9 At some point yesterday as we were
10 talking about the new review. I don't remember
11 if it was in the point of departure or in sort of
12 the 101 thing that Nelson and I did, I made a
13 statement to the effect that in this analysis we
14 were starting from scratch or with a new slate or
15 something to that effect. Let me just clarify
16 what I intended because there was some context
17 there.

18 Back in the fall our AA, assistant
19 administrator, announced that the Agency, the
20 Pesticides Office, would be doing this special
21 reevaluation of atrazine. As part of that, we
22 would do two major things. The first one is

1 focusing heavily on 2003 forward, which is the
2 hundred and plus study that you have all been
3 through and the reconsideration of the drinking
4 water monitoring. The other thing that we
5 committed to do was to ensure that the old risk
6 assessment was safe.

7 There are a lot of ways to interpret
8 that. You can interpret that that you go through
9 every single millions and millions of pages that
10 have been submitted to the Agency and that have
11 been performed by researchers all over the world
12 or other extreme is that you take the overviews
13 and you just pick them up and you go. And I
14 would think that some of you probably had that
15 interpretation or somewhere in-between depending
16 on your personal perspective.

17 I just wanted to make sure that this
18 is what we are doing and it is relevant because
19 of some comments that Penny had commented on
20 yesterday and we wanted to make sure that you
21 understood what we were doing. We have a small
22 army in pesticides terms. They are putting a lot

1 of resources to this and I have the honor of
2 keeping the train on the tracks. Our small army
3 has a very large task in a very short time frame.
4 And so what we are doing is doing what the AA
5 asked of us. We are going to go through the old
6 data in what we consider to be sufficient to
7 ensure that the points of departure and the
8 uncertainty factors in the new risk assessment
9 are safe for human health for every life stage we
10 can find across different durations.

11 That does not mean that we are going
12 to go through millions and millions and millions
13 of pages. What it does mean, however, is that
14 when we select our points of departure, when we
15 come back in September, that we will have been
16 through enough of those pages and pages that we
17 feel confident that we sit here to say that our
18 new proposal is safe. And our new proposal
19 covers all sensitive groups.

20 What that means in practice we have
21 four months to figure out but I can tell you we
22 will start with what we call the data evaluation

1 reviews. Yes, data evaluation records, what we
2 call DERs which are essentially summaries of the
3 studies that come from the guidelines. And the
4 guideline studies are submitted, literally come
5 in volumes. A chronic bioassay can have easily
6 six, seven, eight, volumes. So we are talking
7 mountains of paper.

8 And so what we do is take those
9 mountains of paper and summarize them. And
10 fairly lengthy reviews there can be easily --
11 some of them are 50 pages. We will start with
12 those DERs and go from there. But we will
13 however, focus a great deal of attention on the
14 new studies that are coming in part because we
15 know ahead of time that the doses are lower, the
16 endpoints are precursor events, and so we are
17 pushing the dose responses to the left on the
18 dose response curve. And so that will be a large
19 part of the focus but we will go back and ensure
20 that they are safe, that we are not going to go
21 through every individual animal and submit it to
22 the Agency.

1 SESSION CHAIR PORTIER: Dr. Crisp?

2 DR. FENNER-CRISP: I wasn't wishing to
3 suggest you had to go back and re-review a study
4 from scratch.

5 DR. LOWIT: No and I didn't think you
6 were. We just wanted it on the record.

7 DR. FENNER-CRISP: The point I was
8 making was we may know now something a little bit
9 more about a particular endpoint of concern, its
10 mode of action, whatever, some nuance and/or have
11 reached a stage where we now reinterpret certain
12 kinds of data. And it was that mini task that I
13 was suggesting had to be pursued in addition to
14 looking at the new information.

15 Can I ask a question since I had the
16 microphone? It reminded me in this last thing
17 about the exposure time frame needed to induce is
18 shorter than in the 2003, that refers to the
19 chronic number, I presume.

20 DR. LOWIT: No, I refer mostly to the
21 shorter term.

22 DR. FENNER-CRISP: Oh, okay. That was

1 what I was going to ask you. Do you have in mind
2 now, looking at the other numbers over all of the
3 course of exposure durations, two of the three
4 categories were driven by data related to our
5 discussion the last few days. The pubertal assay
6 drove the middle number, the LH surge drove the
7 chronic number, but these kinds of data did not
8 drive the acute number.

9 So, could we interpret the possibility
10 that you may be looking at this body of data
11 related to the MOA and its consequences for
12 generating an acute number?

13 DR. LOWIT: I don't know. I am not
14 going to answer that.

15 DR. FENNER-CRISP: Okay.

16 DR. LOWIT: I am sorry, Penny, but I
17 am going to answer a different question. I am
18 being flip again.

19 DR. FENNER-CRISP: I think you said
20 that data set wasn't --

21 DR. LOWIT: Yes, and that is an
22 important point and I think we did hear a fairly

1 strong consensus that those single 15-minute, 30-
2 minute cort measures would not make a robust
3 regulatory implant. I think that was one message
4 that we got that was pretty clear.

5 But as I have been sitting here and I
6 went home last night digesting what some of you
7 have been talking, particularly Dr. Krishnan and
8 O'Byrne trying to blend those concepts, as I sit
9 here, I think what we really need is a different
10 kind of assessment. I actually think we are
11 asking the wrong questions.

12 And I think this is, if you follow
13 Kannan's line of thinking around the AUC and you
14 blend that with the chemograph idea. And then if
15 we can do some calculations overlaying AUC and
16 chemograph, there may be a better way of asking
17 these questions. Instead of thinking isolated
18 duration, think about it on an AUC basis. It is
19 a much more sophisticated way of thinking about
20 it and would create havoc for the risk managers.

21 But I think it would bring in some of
22 the ideas that we have heard this morning about

1 bringing in the level of concern idea and
2 thinking about different CWSes that seem to fit
3 in different categories of 20 some that have a
4 lot of hits, and a lot of them that don't have
5 any, and some in-between, and if you get these
6 different patterns. I think we have been
7 thinking about it on an AUC basis. We may be
8 able to get more of a better distribution of that
9 way of thinking.

10 And so how that fits into doing an
11 acute risk assessment in a short-term, or in the
12 30 days, or an intermediate term of up to 60 days
13 or six months or whatever it is, I don't know how
14 that fits but I think it is actually answering
15 the question. And I don't know how to do it but
16 we will figure it out.

17 DR. FENNER-CRISP: The other thing you
18 don't have assembled yet and we talked about it
19 today and a little bit at the end of yesterday is
20 the human biology that is relevant to the results
21 that have been gathered in the laboratory animal
22 studies. And when you have that, it will better

1 inform the point you have just made.

2 SESSION CHAIR PORTIER: I think Dr.
3 Horton and Dr. Akana will want to comment
4 shortly. Short comments.

5 DR. HORTON: Okay, very short comment.
6 I want to summarize some things made by other
7 people that I think all come together and one is
8 Dr. Krishnan's comment about the area under the
9 curve plus Dr. Akana's comment that she made
10 earlier today about the fact that one 15-minute
11 exposure to cort may not be a significant event
12 but multiple exposures might be. So that when
13 you start putting all of that together, it might
14 be a significant event so as to put these things
15 together.

16 And Dr. Cooper's comment that perhaps
17 we have been looking under the light post for the
18 keys and I think we were driven by a mode of
19 action based on the mammary gland tumor and the
20 LH surge but in the result of that, a lot of our
21 thinking and a lot of the experiments have led us
22 to some very interesting results and perhaps when

1 I finally get this figure done, we can kind of
2 move away from the lamppost and think about how
3 to use this new information in an informed way.

4 SESSION CHAIR PORTIER: Dr. Akana?

5 DR. AKANA: Here is an idea for you.
6 You take a small community water system. You are
7 measuring atrazine raw and in finished water.
8 And then in the raw sewage, you measure cortisol.

9 SESSION CHAIR PORTIER: She keeps
10 dropping these gems. I don't know what to do
11 with them.

12 DR. AKANA: It might go with the
13 bootstrap method well.

14 (Laughter.)

15 SESSION CHAIR PORTIER: Dr. Lowit, you
16 know, as I listened to all of this, you are
17 keeping things on track. The train idea. And I
18 keep wondering if these are two trains kind of
19 going along together trying to get in the station
20 at the same time or two trains coming at each
21 other and we don't know if they are even on the
22 same track. So they may come together or they

1 may pass in the night. So it will be interesting
2 to see when we get here in September or October.

3 DR. LOWIT: Well the train I am
4 driving is the one that the data is interesting.
5 So I don't want to sit here and speculate and
6 sort of talk free flow because that is what I was
7 starting to do with Penny.

8 SESSION CHAIR PORTIER: Just thank the
9 panel and let's go.

10 (Laughter.)

11 DR. LOWIT: Yes, I think the point is
12 well taken that we have collectively heard an
13 enormous amount of helpful feedback on a very
14 diverse almost absurdly diverse array of topics.
15 And to say that we appreciate what you have been
16 doing and that what you do whether it is a
17 permanent panel or first timers, it is a lot of
18 work to come to these meetings. We know we hand
19 you lots of pages and ask you to digest and turn
20 around feedback on something you may have just
21 learned about two weeks ago.

22 And I am always impressed when I come

1 to these meetings to the degree to which really
2 smart people come together and do really amazing
3 things and this is just another example of that.
4 And I want to thank each and every one of you on
5 behalf of the whole team.

6 We will be back in September with the
7 next generation of what you have seen with most
8 likely some more choices that we haven't talked
9 about here, points of departure, that sort of
10 thing. We will do a more explicit evaluation of
11 life stage sensitivity that we really haven't
12 addressed here. Peripherally we have but we will
13 head it straight on a little bit more.

14 We will also be joined by your
15 epidemiology colleagues, both on the team and
16 some people on the panel will join us. So we
17 expect a good conversation around thinking about
18 how animal and human information do and don't
19 match. And I can tell you often they don't match
20 and that is a great challenge.

21 So I will thank each and every one of
22 you. I will thank Laura, and Joe, and Charlene

1 and everyone else on the SAP staff. Personal
2 thanks to my team. It is an amazing group of
3 people.

4 SESSION CHAIR PORTIER: Thank you.
5 For the panel, once the DFO makes his final
6 comments, I want you to just leave all your
7 papers and your computer. We are going to go
8 next door for a short five minute process meeting
9 where we talk about how we produce the final
10 report.

11 And at this point, I want to turn it
12 over to the DFO, Joe Bailey, for final closing
13 remarks.

14 MR. BAILEY: All I want to say is to
15 thank the panel for all their hard work, for
16 agreeing to come to the meeting and I look
17 forward to working with you over the next few
18 weeks getting the report pulled together. And I
19 thank EPA for their presentations. I think they
20 were very well done. And I want to thank the
21 public commenters who came to the meeting as well
22 to present their views.

1 And that's it. Thank you.

2 Oh, yes, and we will get the report
3 completed within 90 days from today.

4 SESSION CHAIR PORTIER: Thank you.
5 That ends the meeting.

6 (Whereupon, at 12:14 p.m., the
7 foregoing meeting was adjourned.)

8
9
10
11
12
13
14
15
16
17
18
19
20
21
22

A				
AA 159:18 161:4	96:3 115:7,13	Administrative 3:2	168:5,12	anomalies 24:6
ability 62:4 122:2	133:19 137:22	administrator	Akana's 167:9	answer 34:18 72:8
128:14	146:9	159:19	al 32:17 40:4 41:7	82:16 97:6 102:10
able 5:14 30:15	acute 7:16 18:8,12	advance 136:15	145:3	125:15,17 135:22
44:7 71:11 118:12	18:19 22:10 50:20	advantage 76:10	Alan 86:10	164:14,17
121:11 141:1,14	52:5 79:17 164:8	91:3	Alkaloids 26:1	answered 117:14
143:6,10 144:21	164:12 166:11	advantages 137:6	allocate 108:15	117:15
145:7 146:21	adapt 112:14	adverse 7:1 17:20	allow 141:21 143:2	answering 166:14
148:22 154:17	adapted 18:3	18:3 22:20 25:21	aloud 24:19	answers 39:19
155:16 166:8	adapting 17:19	25:21	altered 15:8	103:13
absence 130:5	adaptive 22:9 23:2	advice 69:21 70:5	alternatives 40:5	anybody 116:14
absolute 45:16	108:17 110:15	Advisory 1:4 4:4	amazed 85:16	158:5
72:15	111:13 113:10	affect 104:17	amazing 33:13	anymore 85:5
absolutely 22:21	124:19	afraid 33:9	170:2 171:2	anyway 125:6
46:19 63:1 85:16	add 20:12 45:15	afternoon 6:9	ambiguous 8:6	apart 41:2 50:11,21
140:11 148:5	83:15 84:14 103:4	20:15 23:11 31:15	American 147:11	83:7
159:3	107:2 114:5 117:7	agency 1:1 8:19,21	amino 113:18	apologize 55:22
absorption 15:17	124:1 135:6,8	9:4 14:9 29:13	amount 13:4	126:10 136:14
83:22 112:4	150:19 157:21	88:10,19 89:13	102:15 129:11	apparently 24:8
abstract 115:2	added 154:6	102:13,17 107:10	144:15 147:5	appeal 93:20
absurdly 169:14	adding 154:10	116:15 125:21	169:13	appear 18:14 22:8
acaricide 23:9	addition 34:7	136:17 137:13	amounts 105:10	45:12 114:13
acceptable 134:6	163:13	142:7 149:11	AMP 65:12,18	appears 18:2 64:13
135:20	additional 6:7 8:7	150:18 157:5	76:10 97:11 98:1	appendix 92:7,7
accommodating	39:22 74:3 105:16	158:13 159:19	amplitude 97:12	100:14 140:5,8
18:10	106:7 108:5,8	160:10 162:22	analogies 28:19	applicable 63:2
accompanied 35:2	109:1 120:8	agency's 124:12	analogous 39:19	114:11 118:22
account 103:8,15	123:22 125:14	137:10	50:8	application 82:8,9
103:21 148:19	133:3 135:6 152:9	ages 23:19,19	analyses 58:6	82:12 83:8 90:16
accounting 119:5	157:13	aggregate 124:15	analysis 7:13 16:19	107:6 116:7 124:2
accounts 107:7	Additionally 19:2	ago 6:13 55:22	34:1 40:1 53:11	130:2 139:2
accumulated 101:8	130:7	78:21 113:2	72:7 76:2 87:11	applications 82:22
accuracy 145:18	address 7:20 74:1	122:12 158:12,18	113:22 116:17	applied 7:19 47:22
accurate 146:22	115:19 123:6	169:21	119:17 143:15,22	48:2,6 101:16
accurately 139:22	addressed 33:2	agree 22:16 25:20	159:13	129:11
acknowledge 73:18	59:6 122:19,22	61:12 74:11	analytical 116:6	apply 103:19
acronym 66:12	170:12	129:22 132:5	and/or 137:15	114:20
act 1:4 10:2 107:5	addressing 150:16	agreed 14:5 133:12	163:10	appreciate 28:15
action 7:4 8:8 9:10	adds 154:16	agreeing 171:16	animal 1:6 24:18	63:17,19 136:2
9:10,12 22:13	add-on 125:5	agreement 133:4	25:2 107:22	169:15
26:7 29:20 163:10	adequate 115:19	agricultural 46:1	162:21 166:21	appreciation 158:8
167:19	adequately 143:21	82:6 130:15	170:18	approach 38:3
actions 7:6	Adjourn 3:22	ahead 157:1 162:15	animals 7:8 24:3	42:20,21 87:12
activated 121:19	adjourned 172:7	aid 8:19 144:17	127:16	89:15 91:12 101:3
activation 27:14,18	administered 23:10	Akana 2:2 62:10,11	Anna 107:2	101:4,14 102:3
actual 22:7 60:18	administrations	63:3 79:13,14	announced 159:19	114:17 115:12
	15:18	98:21 167:3 168:4	annual 111:14	116:11 118:8

119:11 121:6,12 123:7 126:1 131:6 137:11 141:3,6,9 142:14,15 144:13 148:10 152:14,19 approaches 3:9 32:8 89:12 91:10 91:14 99:20 100:4 113:11 114:15 133:16 136:17 137:17 141:11 appropriate 9:6 19:8 26:21 27:2 72:12 83:20 84:1 95:7,22 96:15 116:7 appropriately 124:12 approximately 37:9 55:19 April 1:13 34:9 37:17 arbitrary 155:9 architecture 8:14 area 16:7 26:14 27:2,8 74:11 130:12 167:8 areas 10:8,9 77:3 argue 123:12 argument 27:20 95:10 112:18 arguments 28:1 arises 17:6 army 160:22 161:2 array 169:14 arrival 130:9 arrows 9:16 13:2,7 articles 149:22 artificial 140:4 artificially 81:13 aside 66:11 asked 6:1 7:6 25:14 32:11 58:21 69:9 76:8 96:22 161:5 asking 68:21 69:20 70:5 77:7 165:11 165:16	asks 148:17 aspects 15:16 assay 20:19 113:18 164:5 assembled 166:18 assessment 5:20 6:22 7:10 9:5 18:9 25:13 74:14 88:3 95:5 123:10 137:5 160:6 161:8 165:10 166:11 assessments 95:1 122:18 assign 126:16 assigned 4:22 126:15 assistant 159:18 associated 15:13 16:13 18:17 24:16 119:14 151:21 Associates 58:8 Association 147:12 assume 45:21 assumes 127:22 135:17 Assuming 104:5 assumption 74:13 92:18 assumptions 118:9 atmospherically 129:17 atrazine 1:6 4:5 9:5 10:2 11:7,14 15:5 15:11 16:3 23:7 28:9 35:17 36:13 37:6 40:22 76:8 76:11,17,20 77:2 77:9 79:18 80:13 82:8,22 85:10 86:6,7,13 89:3 90:15 95:1,15,20 98:14,18 106:10 107:4 110:5 112:9 113:19 118:21 128:6,14,21,22 129:3,10,14,15,16 130:5,17 131:1,13	132:13,15,18,19 137:2 159:21 168:7 ATS 1:22 attached 126:19 attempt 10:7 attention 124:6 162:13 AUC 165:13,15,18 166:7 AUCs 16:5 audience 4:14 12:22 augmented 64:20 65:20 auto 156:14 autoregressive 141:2,4,8 154:7 available 124:4 149:7 average 16:5 18:21 30:5,10,12 38:20 38:21 51:12 52:20 53:18 66:9 67:11 69:2,4,6,8,12 77:19,20 79:1,3 90:3 116:3 118:4 126:6 132:1,3 134:11 135:3 138:8,9,14 139:15 139:15 151:12 152:13,15,17,19 152:22 153:2,7 157:11 averaged 78:10 averages 36:20 59:4,6 66:4,7,21 67:1,1,4,21 68:9 71:10 79:8 93:8 93:19 112:17 118:3 138:8 139:14 146:11 152:21 averaging 71:22 81:7 88:18 93:19 112:13 awful 130:14	axis 17:8 27:15 137:3 a.m 1:15 4:2 85:1,2 <hr/> B <hr/> back 5:7,18 6:4,10 7:12 12:4 17:15 18:1,2 19:9,19,19 24:22 25:5 31:20 35:11 37:18 43:20 55:14 60:8 67:17 68:11,15 72:13 74:8 77:11 78:4 80:20,21 83:2,13 109:9 110:7,11 120:14 123:13,16 159:18 161:15 162:19 163:3 170:6 background 39:7 40:3 81:14 bad 80:14 119:8 Bailey 2:22 3:3 4:3 4:6 64:11 171:12 171:14 balanced 139:18 ballpark 108:22 Ballroom 1:15 band 104:3,8 bands 103:7 bare 119:15 BARRY 2:3 base 20:17 142:2 based 14:17 16:5 18:15,22 19:6,15 20:10 21:1,3 34:5 34:8 39:6 42:8 74:14 92:11 101:7 107:9 118:1 157:1 167:19 basic 116:10 137:21 140:21 141:19 142:22 143:6,13 basically 41:1 42:14 72:12 73:1 91:15 100:5	basin 128:7,13 129:4,5,10,16 130:10,13 131:9 basing 20:19 101:4 112:17 basins 131:7 132:8 basis 19:7,16 72:16 73:12 84:15 103:18 134:14,18 165:18 166:7 Bayesian 94:15 beginning 25:12 49:18 78:22 behalf 158:7,10 170:5 behavior 23:2 119:13 believe 70:10 92:16 131:13 bells 105:5 belt 11:20,20 benchmark 7:13 19:5 28:4 best 63:13 68:5,5 74:18 75:13 86:16 better 32:12 33:12 68:17 69:19 73:20 76:4 88:5 120:4 139:9 143:8 148:22 165:16 166:8,22 beyond 64:3 biased 97:21 BIC 140:22 big 48:13 78:12 85:18 91:14 97:1 101:13 105:1 114:1 131:3 158:15,15 bigger 33:9 billion 62:17 97:16 105:3 bin 52:9 bins 46:17 bioassay 162:5 biological 157:4,7 biology 116:15
---	---	---	--	---

166:20	brain 12:7 27:4	119:18 120:1	chair 1:17,18,20,21	changes 11:4 17:7
Biscoe 110:4,4	break 31:7 84:17	122:2 156:18	4:7,9 6:12,15	33:13 128:9,16
bit 7:3 8:6 14:19	brief 85:8 128:20	157:3	10:13,19 11:22	changing 50:1
18:20 26:14 47:16	briefly 32:22 34:11	captured 4:18 5:8	12:8 13:10 14:12	characteristics
59:22 92:22 93:14	72:5 140:7	12:17 61:17 67:12	20:11 21:22 22:14	59:2 72:19 101:5
93:17 110:7 122:1	bring 13:8,12 25:16	captures 25:1	23:6 24:10 25:10	characterize 89:1
139:9 163:8	30:20 74:6,8	capturing 49:13	27:10 29:12 33:6	126:1
166:19 170:13	101:11 119:12,14	56:12	37:14 40:6 43:19	characterizing
bi-weekly 50:4	122:21 165:21	carbon 86:7,14	44:19 45:2,19	143:21
Blair's 27:19	bringing 96:5	121:20 122:2	46:7,8,14,16 49:1	charge 3:6,8 8:18
blend 165:8,14	117:8 149:6 166:1	careful 27:21	53:14 54:2,7,10	60:9 113:8 137:20
blended 74:16	Brits 37:6	carefully 98:5	58:2,5,13 60:5	charged 153:22
block 23:14	broad 127:19	CARMEN 2:16	62:8 63:20 70:20	Charlene 170:22
blocked 23:12	brought 98:21	carries 138:7	70:21 71:13 72:2	chart 11:7
Blomquist 41:6	113:8 124:20	cascade 26:6	73:7,15 74:2	chemical 15:19
blood 26:14	140:8 157:20	case 13:8 17:3 25:4	79:13 81:11 82:3	16:11 110:5 146:8
blue 75:3 76:18	BS 74:7	36:18 52:11 56:19	83:14 84:16 85:3	chemicals 7:21
77:16 79:2	Bucher 1:21 13:10	71:21 88:5 92:17	87:21 89:17 94:4	130:16
BMPs 128:13	13:11 22:14,15	96:14 118:13	94:12 99:15	chemograms
board 2:1 27:1	25:20	141:19 143:3	102:19 103:3	138:20 144:8
Bob 20:3 58:8 76:6	buggy 77:15	cases 48:10 57:13	104:19 105:8,13	chemograph 42:8
87:5 118:20	built 106:5 124:4	95:20 100:18	105:18 107:15	45:3 64:18 65:20
body 15:5 41:9	146:6	124:20 143:9,10	108:5,8 109:3,12	77:16 119:16,20
83:21 164:10	bunnies 25:15,18	cast 14:7,10	109:15,22 110:12	147:16 149:1
bootstrap 66:11,20	burden 38:14	catch 105:7	111:11,16 112:2	151:16 165:14,16
67:3 168:13		categorical 100:12	112:22 114:4,21	chemographs 45:8
bootstrapped	C	categories 100:6	116:20 117:5,10	45:10 68:6 99:2
67:20 70:22	C 140:6,9	164:4 166:3	120:8 123:9	105:2 119:13
bootstrapping	calculate 19:22	categorized 140:15	125:13,18 126:13	155:17
141:11,13	42:12	category 101:1	132:22 134:19	chemograph(Sec...
bothers 119:1	calculated 16:5	147:3	135:7,9 136:4,8	137:14
bottled 81:16	42:7 66:3	caught 10:22	137:18 149:13,18	Chen 32:17,17,17
bottom 11:3,13	calculations 19:18	causes 17:22	150:21 152:9	40:3 42:4,5,5,16
bounce 17:15	20:6 165:15	cautious 24:11	154:22 156:5	44:13,14 45:14,14
bounces 18:1 24:22	calendar 37:12	caveat 107:20	157:8,16 163:1	children 9:2 10:17
bound 127:6	38:15	center 52:3	167:2 168:4,9,15	chlordimeform
bounds 69:21	calibration 146:13	centile 34:19 41:21	169:8 171:4 172:4	23:9
70:17 89:13,19	call 6:2 16:18 66:12	42:13,13 43:4,9	Chairman 32:2,21	chlorinated 16:3
91:2 99:21 100:2	86:1 125:6 151:17	centiles 33:17	40:20 47:7 63:8	chloro 84:2
100:19 101:10,21	161:22 162:2	35:19	challenge 89:22	chloroforms 16:2
102:16 104:18	calling 64:22	central 11:12 93:21	170:20	chlorotriazines
114:19 126:5,8	cancels 45:17	139:20	CHAMBERS 1:22	76:9,13,21
133:5,13 135:1,2	cancer 13:15	certain 59:8 81:6,7	chance 134:13	choices 170:8
141:22 151:22	capabilities 11:13	121:21 123:17	158:3	chooses 125:11
Boy 80:17	capture 6:7 12:21	163:11	change 54:21 128:4	choosing 110:20
BPA/BPH 105:5	21:16 22:11 30:15	certainly 64:11	128:5,5,9,14	chronic 18:9,12,16
Brady 64:2	30:18 73:9 87:13	84:14 92:9	changed 128:17	80:12,12 162:5

163:19 164:7 circles 76:20 citizen 153:21 citizens 153:17 CI 16:4 clarified 11:9 20:9 43:11 clarify 10:14 32:3 32:11 33:20 62:12 63:18 102:20 126:11 159:8,15 clarifying 4:20 31:13 clear 4:17 20:20,20 25:8 26:20 37:4 47:14 94:7 111:12 117:20 120:19 135:21 149:20 165:4 clearance 23:11 clearly 16:13 24:16 24:18 61:9 112:15 138:4 climate 111:19,22 112:7 121:7 128:9 close 5:14 47:20 48:5 142:13 157:17 closely 84:4 146:15 closing 158:4,6 171:12 clusters 80:3,16 Cmax 16:11 CNS 11:2,8 code 111:5 coffee 31:7 coherent 57:22 cold 128:10 colleague 131:20 colleagues 15:15 127:11 134:21 139:4 170:15 collect 109:1 117:3 117:4 collected 118:1 collectively 31:4 56:3 169:12	College 150:9 color 111:5 column 53:16 combination 141:18 146:7 combined 15:14,20 129:9 combining 145:6 145:22 149:2 come 5:7 8:4,9 14:3 18:13 38:19 60:8 67:16 72:5 90:14 99:13 102:10 126:19 161:15 162:3,4 167:7 168:22 169:18,22 170:2 171:16 comes 11:14 28:20 72:1 91:15 107:4 121:15 134:17 comfortable 91:7 116:14 comforting 93:5 coming 57:21 72:13 83:4 86:20 122:1 133:6 162:14 168:20 comment 12:10 29:16 58:20 62:9 63:9 72:5 89:15 108:9 113:7 114:14,18 115:12 126:4 136:16 137:6,10 153:11 157:21 158:20 159:5 167:3,5,8,9 167:16 commented 160:19 commenters 171:21 comments 4:20 7:11,22 14:22 22:16 26:13 74:4 86:11 104:21 105:16 108:6,7 115:2 120:9 123:22 131:5	152:10 154:21 157:13,19 158:6 160:19 167:4 171:6 committed 160:5 committee 126:11 common 49:11 96:11 134:8,14 community 34:8 36:10,12,17,22 39:3 41:12 48:4 76:1 86:4 87:9 96:6,12,19 98:2 98:10,13 99:11 106:13 109:6 121:16 125:2 131:15 143:5 144:4 151:6 168:6 comparable 55:19 compare 7:14 37:2 50:18,21 51:6 133:9 compared 42:1 43:22 67:9 107:21 comparing 106:15 126:6 comparison 51:20 56:5 107:20 108:3 compelling 13:19 13:20 competence 69:15 complete 14:21 completed 172:3 complex 9:20 12:15 73:9 82:16 complexity 154:16 154:17 compliance 125:6,8 complicated 13:22 93:9 141:5 144:2 146:18 complication 17:5 135:4,6 component 154:7 components 76:12 composites 156:15 157:11	comprehensive 149:17 compute 104:18 computed 34:20 36:21 41:20 53:6 computer 46:21 171:7 concave 138:16,18 138:22 concentrate 118:19 concentrated 90:17 concentration 26:15 27:1,9 30:8 36:19 42:11 97:5 97:22 100:19 101:9,20 102:7,12 103:2 113:15 114:18 115:19 116:12 122:3 129:22 130:3,8 131:1 136:19 150:17 157:12 concentrations 19:8 59:4,5,12 77:20 88:13,16 89:3,8 95:2,11,12 98:7,17,19 101:5 116:2 121:21 129:18,21 145:3 concept 115:4,6 concepts 165:8 conceptualized 9:12 concern 24:13 30:13 45:20 89:16 90:18,22 97:1,3,6 102:2 105:1 126:8 132:21 135:1,16 135:21 146:16 163:9 166:1 concerns 6:1 18:13 concluding 4:16 conclusion 40:7 43:20 44:12 conclusions 43:21 concordance 29:8 concur 134:20	135:12 conditions 150:7 150:12 confidence 9:17 34:22 39:16 88:13 89:13,19 91:2,4 99:21 100:2,18 101:10,21 102:16 103:7,16 104:3,8 104:18 114:19 125:22 126:5,8 127:11,12 133:4 133:13,20 134:22 135:2,15 confident 60:22 112:20 161:17 confidently 100:9 confirmation 58:6 confirmatory 118:14 confused 20:8 confusion 52:3 135:16 confusions 19:13 conjecture 82:19 conjunction 88:8 connection 19:19 consensus 165:1 consequence 120:3 consequences 164:11 conservative 88:1 92:16 93:6 96:2 133:7 consider 26:11 27:6 65:2,8 89:13 97:20 99:20 137:13 161:6 considerable 13:3 95:10 consideration 9:13 14:16 15:6,10 16:18 17:6 89:20 108:3 considerations 15:3,15 16:9 114:20
--	--	---	--	---

considered 22:20 27:17 65:6 93:16 108:2 137:2	62:12 140:14	21:15 23:10 28:11 30:2,12,16 72:9 72:15 140:20 149:11	42:8 43:4,9 48:5,7 48:16 52:6,6 53:20 56:21 57:11 57:21 59:11 60:21 60:22 62:6 72:16 73:5 77:17 79:2 90:2 104:5,13,15 105:1,4 118:1,2 119:4 131:19 156:19	143:1,5 146:11 149:4 150:15 156:11,14 161:6 161:22 162:1 163:12 164:4,7,10 164:20 169:4
considering 84:10 89:18 125:22 137:1	correlated 147:13 147:16	criticism 86:1 87:18	danger 138:12	database 7:12 56:12 57:20,21
consistently 98:14 99:13	correlation 92:19 93:13 121:10 143:17 144:1,6	criticize 85:13	DANIEL 1:23 2:15	dataset 62:18 65:3 65:15,16
constituent 128:1	cort 165:2 167:11	CRM 110:5	dark 75:3 76:18	datasets 73:19 75:14 87:3 92:13
constituents 132:16	cortical 15:9 17:4 17:14 24:15	crop 128:9	data 8:2 9:3,13,15 13:9 17:7 27:14 27:22 28:2,7,19 32:9,11 34:3,3,4,5 34:8,12,13,17 35:20,20 36:1,9 39:6,6,8 41:2,3,8 41:12,14,16,18 42:15,15,19 43:11 45:6,21 46:1 48:5 48:7,8,14,17 49:3 50:19 51:7,15 57:12 58:15 62:13 62:15 63:14,14 72:7 73:1,5 74:18 77:6 78:5,8,16 82:20 87:7 88:21 88:22 89:10,14,20 90:3,3 91:16 93:21 94:22 95:1 95:4,7 96:6,17,20 97:12,15,20 98:1 99:7,22 100:1,5,8 101:7 102:8,21 106:1 109:2 114:11 115:7,13 115:18 117:2 118:1,15 119:4 120:18,19 121:1,6 121:7,7,9,13 124:4 126:3 127:6 131:8 132:4 137:2 140:3 141:21,22 142:4,16,18,21	deal 5:20 29:13
construct 118:16	cortisol 168:8	CropLife 95:6		
consumption 15:13 123:13	country 77:4	crops 112:4,9		
contained 66:20	Coupe 2:2 94:5,6 94:14 109:11,18 116:20,21 126:13 126:18 127:1,9 133:4 149:14,15	cross 112:11		
contaminants 118:22	couple 55:21 98:22 102:5 105:14 150:10 152:14 159:1	Crowne 1:15		
content 95:17	course 15:4,7,11 16:22 17:4 40:2 49:16 53:8 56:17 63:10 64:3 73:20 90:11 96:21 111:4 111:18 131:9 164:3	current 9:3 17:5 55:4,17 111:1 141:2		
contention 74:12		curve 26:14 27:2,8 84:7 138:15,17 140:13 141:21,21 142:11,13 143:21 144:14 162:18 167:9		
context 10:2 26:12 79:10 84:13 106:3 141:9 145:2 159:16		curves 16:7 138:13 138:22 144:15		
continue 86:8		CWS 49:8 51:14,20 56:3,6,11,14,17 56:22 59:17,17 61:15 68:14 69:18 71:15 109:10 110:10		
continued 3:7 122:15		CWSes 49:6 166:2		
continuum 123:15 133:16 134:3		CWS's 48:1 153:18		
convened 1:15		cycle 18:1 24:22 28:6,7 29:5 79:19 79:20,21 80:1 111:15		
conversation 170:17	covariates 148:20	C-O-N-T-E-N-T-S 3:1		
conversations 11:10 27:12	covered 99:18 150:7 158:1			
conversely 126:8 131:9	covering 56:15			
convex 139:1	covers 161:19			
convinced 130:16	Crawford 100:13 115:6 131:6			
convincing 18:15	create 36:18 41:19 44:9 68:14 101:5 115:22 132:4 165:20			
Cooper 12:8,9 23:6 23:7 30:19	created 38:3,20 72:11,17 81:18			
Cooper's 167:16	creating 127:5,5			
corn 77:3	creation 80:22			
corner 94:7	Creek 45:22,22			
correct 14:22 23:4 25:4 49:5 58:12 63:1,7,10 127:3,8 139:5 140:11	Crisp 11:15 12:1 163:1			
correctly 46:19	critical 18:5,8			

D

D 2:7
DABT 1:21,22 2:4
 2:13
daily 30:5 36:19
 41:2,8,13,13,13
 41:14,17,17,21

48:13 71:9,12 157:4,5 162:13 dealing 12:16 28:3 Dear 126:20 decent 92:2 decide 26:17 77:14 78:16 decided 78:5 79:16 95:4 decision 90:7 decisions 113:20 150:13 decision-making 125:4 decrease 138:15,16 138:18 139:3 decreases 136:22 155:8 decreasing 110:22 153:4 Dedrick 20:3 defend 73:12 define 6:21 7:2 72:14 73:2 75:13 75:14 102:12 defined 61:5,9 87:6 106:1 116:12 124:8 definite 141:16 definitely 71:9 103:21 definition 142:20 degree 10:1 170:1 delay 23:18 delayed 23:13 24:6 24:17 DELCLOS 2:3 deleterious 80:10 demonstration 25:1 dense 48:16 92:13 102:21 133:19 denser 73:2 departure 89:1 159:11 161:7,14 170:9 departures 9:1	depending 18:5,7 79:8 89:16 90:6 95:15 99:9 108:19 160:15 depends 60:16 81:9 85:17 104:3 derived 20:4 67:2 107:14 126:2 127:15 deriving 19:8 DERs 162:2,12 describe 39:22 114:12 140:9 described 34:13,22 89:6 115:6 125:20 136:18 137:12 140:5 describes 137:21 describing 36:8 design 37:22 102:11,18 116:16 130:21 157:1 Designated 2:22 4:6 designed 130:18 designs 37:4 destruction 27:20 detail 8:4 34:13 36:8 84:13 148:13 detailed 33:17 details 127:10 detect 80:16 detected 76:17 129:4 detections 89:9 determination 144:18 determine 94:22 127:21 determining 9:3 88:12 89:13 99:21 114:19 130:17 144:19 deterministic 141:13 146:6 develop 8:22 9:4 87:11	developed 13:18 118:21 147:7 developing 36:9 development 13:14 21:19 22:6 24:6 28:1 developmental 22:3 deviation 108:16 deviations 43:10 DFO 171:5,12 diagram 9:19 10:7 10:22 22:3 dietary 122:19 differ 90:6 144:16 difference 7:7 13:4 22:3 39:1 58:14 58:17,17 70:7 79:7 83:5 94:15 95:10 97:2 131:3 140:16 142:8 differences 56:13 124:21 different 9:16 10:3 10:6 22:11,13 32:10 47:17,21 56:7,16 61:4 70:5 77:4,5,8 83:8 88:15,17,19 103:12,13 112:11 127:15 133:21 143:18 148:9 159:7 161:10 164:17 165:9 166:2,3,6 differential 108:11 differentiated 47:16 differs 90:1 difficult 12:22 21:14 28:17 29:9 144:7 digest 169:19 digesting 165:6 dilution 85:20 dip 111:4 direct 101:18	direction 124:12 136:1 149:11 directly 34:20 96:13 146:11 director 158:17 directors 158:18 disadvantages 137:7 disagree 22:21 23:3 104:9 discontinuous 122:4 discount 142:11 discussed 9:11,13 9:15,18 42:22 88:10 110:8 130:22 142:6 discussing 9:21 60:9 discussion 4:11,12 6:3 19:3 47:3 64:5 74:9 77:12 83:16 84:20 114:2 131:18 150:4 164:5 discussions 5:6,7 8:2 13:13 17:10 17:17 20:10 28:13 distinction 86:2 87:17 distinguish 74:11 distribution 43:6 44:7 59:5,5 61:1 66:22 67:20 91:3 91:4,8 128:1,6,21 128:22 166:8 distributions 40:12 59:2 89:11 147:7 diverse 169:14,14 divide 11:19 93:11 division 122:7 docket 1:10 31:11 33:18 40:5 43:15 47:11 55:21 document 8:22 12:5 documents 92:4	doing 26:16 30:16 32:14,15 44:5 46:20 55:10,18 74:13 104:5,11 107:11 116:2 120:3,4 122:17 127:11 142:5 152:15 153:2 156:15 158:9 159:20 160:18,21 161:4,4 166:10 169:16 Don 64:2 136:3 door 171:8 dose 15:12 16:8 17:2 19:14,15 21:4 23:10 24:7 26:17 28:22 29:3 30:12 81:22 83:18 83:20 84:1,5,6,12 105:1,5 162:17,18 dosed 24:3 doses 162:15 dosing 17:21 double 81:18 82:4 downstream 6:20 Dr 4:7 6:1,1,11,12 6:17 8:3,8,12,13 10:11,14,21 11:15 11:15,16,22 12:2 12:8,9 13:10,11 14:13,15,21 20:11 20:13 21:2,7,14 21:21,22 22:1,9 22:14,15 23:6,7 24:1,10,11 25:10 25:11,20 27:10,11 30:14,14,19 31:1 31:2,21,22 32:16 32:17,17 33:8 35:3,7,8,9,13,14 35:15,16 37:16 39:11,13,18,18 40:2,3,13,17 41:4 42:2,4,4,5,14,16 42:17,18 43:8,13 43:13,13,16,17
---	---	--	--	---

44:13 45:1,9,14 46:3,9,12,15,19 47:6,6 49:5 52:17 52:18,22 53:1,2 53:22 54:4,9,12 56:1 57:17 58:3,3 58:12,16,21 60:6 60:7 61:12,12 62:10,11,19 63:3 63:7,8 70:20 72:2 72:4 73:11 79:13 79:14 82:2 83:14 83:15 85:5,7 89:17,18 94:5,6 94:14 98:21 99:16 99:17 102:22 103:3,4 104:21,22 105:8,9,16 107:2 107:15,19 108:7,7 108:9,10 109:11 109:18 111:10,14 113:6,7 114:21,22 116:20,21,22 117:5,6,10,11 123:22 124:1 126:13,18 127:1,9 132:22 133:1,4 134:19,20 135:7,8 137:18,19 145:4 145:12 147:8 148:1,4 149:8,14 149:15,18,19,20 150:21,22,22 153:11 154:9,21 155:14 156:5,7 158:6,7 163:1,2,5 163:7,20,22 164:13,15,16,19 164:21 165:7 166:17 167:2,3,5 167:8,9,16 168:4 168:5,12,15 169:3 169:11 draft 8:22 12:5 drainage 46:2 drainages 82:6 draw 58:10 117:22	155:4 drinker 157:9 drinking 1:7 9:7 15:14,18 35:18 44:16,17,20 57:13 63:12,13 81:16,17 84:10 85:11 87:20 88:14 89:3 96:8 99:8 122:11,12,17 122:19 123:4 137:8 150:10 160:3 drinks 157:10 drive 18:8 164:8 driven 102:11 164:4 167:18 drives 77:15 83:21 driving 100:8 169:4 drop 54:18 dropping 168:10 drove 164:6,6 dry 83:12 due 130:8 duration 5:21 7:17 19:10 22:7 30:7 59:14,20,22 89:16 97:1,3,6,8 102:2,7 150:5 165:18 durations 58:22 59:18 60:3 88:19 137:9 161:10 164:3 dying 158:5 dynamics 98:9,16 D.C 1:17 <hr/> E <hr/> E 1:22 2:22 earlier 58:1 110:8 128:11 131:18 147:9 167:10 early 31:18 75:18 84:7 eased 97:7 easiest 91:1 easily 162:5,10	easy 64:16 67:18 134:16 eco 41:14 44:17 55:19 ecological 44:18 96:21 113:3 ecosystem 57:14 effect 18:6,8 19:11 21:4 22:19,21 23:14 24:5 26:3,8 77:9 79:22 105:11 159:13,15 effective 92:20 93:3 effectively 124:3 effectiveness 95:14 121:17 148:9 effects 1:6 18:12,14 18:16 19:6 22:4,7 24:13 25:3,20,22 26:3 56:16 69:1 84:4 122:20 137:4 157:4 efficient 33:2 155:7 effort 20:2 118:19 151:8 efforts 152:5 eight 8:7 97:18 158:12 162:6 either 6:16 54:15 104:13 126:5 153:4 156:15 elaborate 8:10 elevated 89:8 elevation 74:8 eliminate 52:3 141:1,7 embryo 24:6 empirical 106:1 144:7 encapsulate 22:2 encapsulating 9:9 encroach 81:5 ended 47:18 129:11 endocrinologists 11:18 endorsement 139:20	endpoint 7:9 20:20 130:22 163:9 endpoints 6:21,22 7:13,14 21:16 137:1 162:16 ends 172:5 energy 101:16 enormous 169:13 ensure 131:11 153:15 160:5 161:7 162:19 entire 7:12 10:17 36:1 50:13 56:15 entirely 60:17 entitled 39:15 40:18 environment 131:2 environmental 1:1 113:4 envision 133:17 EPA 1:1 4:20 5:3 32:8 41:7 61:3 91:11 95:4 96:7 97:14 100:15 105:19 110:9 122:7 129:20 134:9 147:19 158:4 171:19 EPA's 81:19 EPA-HQ-OPP-2... 1:10 epidemiology 170:15 episodic 80:11 equal 19:22 38:6 68:12 equally 62:13,17 equivalence 7:19 equivalents 20:5 26:18 error 68:3,7,18 103:10 119:5 142:12 156:1 errors 141:2,4,8 especially 9:20 12:17,22 23:15 46:3 93:18 97:20	99:6 essentially 15:6 16:9 17:1,9 84:3 108:14 144:13 145:4,5 162:2 establishing 61:13 estimate 52:13 60:22 63:4 81:4,6 81:8 90:2,4,9 91:16 93:7 95:22 96:2 97:9 100:2 100:10,18 103:20 104:3 124:9 133:17 135:17 139:22 144:6,7,22 149:4 estimated 42:3 79:2,4 89:21 103:17 estimates 34:19 41:21 89:14,19 101:8 126:2,6 133:14,20 140:21 estimating 44:5 88:15 134:18 142:1 154:17 estimation 134:14 144:9 148:22 estrogen 28:22 29:3 et 32:17 40:3 41:7 145:3 evaluate 8:19 61:10 72:10 73:3 95:8 96:16 134:15 evaluated 14:5 84:12 124:19 evaluating 3:9 9:1 13:15 87:12 124:11 137:7,11 137:16 148:8 evaluation 40:4 84:13 161:22 162:1 170:10 evaluations 84:15 evening 6:8 event 122:5 130:2,3
---	---	--	--	--

167:11,14 events 6:21 7:15 8:5,7 10:4 15:7 16:22 26:6 42:10 82:9 83:6,21 88:17 112:12 147:7 162:16 eventually 125:10 everybody 88:4 116:4 135:17 evidence 8:22 9:14 9:17 13:4 20:21 85:13 105:10 evident 150:6 exact 142:11 exactly 32:11 34:1 50:6 53:22 135:14 139:19 151:9 examine 23:18 examined 32:9 examining 88:17 example 15:17 16:2 17:14,18 26:1 43:7 45:5 50:7 51:11 55:18 65:9 65:13 66:4 74:21 75:1 81:2 115:15 128:10 140:4 142:15 145:2 170:3 examples 100:14 115:17,17,20 116:5 124:21 138:20 143:5 150:8 exceed 30:5 59:8 68:12 98:8 exceedance 133:22 exceeded 134:13 exceeding 134:7 Excuse 84:16 110:1 exercise 43:21 exercises 64:15 65:19 exhausted 29:2 exist 114:13 144:1 existing 13:9 55:11	100:5 124:4 150:8 150:15 exists 118:12 expand 123:5 expect 44:4,22 70:2 75:8,22 100:19 170:17 expected 53:2 71:3 97:4,22 101:20,21 110:22 expensive 86:14 experience 132:13 experiment 17:9 60:15 61:3 73:14 experimental 1:6 28:19 experiments 17:17 25:15 60:13 72:16 100:7 115:9 167:21 expertise 130:15 explain 77:13 130:5 explained 123:15 129:1 explains 129:7,8 explanation 47:9 53:5 explicit 107:14 170:10 explored 94:2 exposed 98:17 exposure 7:17 16:1 18:19 21:7,11 22:5,7,10,19 35:17 36:5 39:15 39:17 72:10 78:1 78:3,13,13,14 79:16 80:11 89:14 89:19 94:22 95:5 95:8 96:1,3,16,19 96:21 99:21 107:8 107:17 118:20 122:18 126:2 133:14,17 135:17 135:17,19 137:3,8 163:17 164:3	167:11 exposures 17:13 18:16 40:19 78:11 122:19 167:12 extended 15:20 100:15 extent 9:3 67:15 122:16 137:12 external 84:6 extra 79:22 extraordinarily 12:15,21 extrapolate 28:14 28:18 extrapolating 117:1 extreme 37:7 91:17 92:15 93:17 113:16 147:4,6,13 153:22 154:1 160:12 extremely 130:1 extremes 59:21 eye 122:15 <hr/> F <hr/> F 2:2 fact 12:7 13:12 22:18 87:10 96:5 97:22 123:2 129:3 167:10 factor 7:19 57:9,16 129:13 factors 28:12 95:15 106:2,4,6,22 127:15 133:6 137:13 148:18 161:8 fail 121:20 fair 144:15 147:5 fairly 48:16 152:1 152:13 162:10 164:22 fairness 32:5 fall 159:18 familiar 147:19 far 73:22 78:3 83:7	93:12 99:1,22 144:2 150:14 154:3 156:12 farmer 82:17 83:2 83:11 fast 111:8 feasible 110:19 111:1 February 37:10 Federal 1:3 2:22 4:6 feedback 9:22 10:5 88:19 111:13 169:13,20 feel 116:14 117:12 161:17 felt 8:5 21:10,18 157:20 Fenner 11:22 FENNER-CRISP 2:4 12:2 163:2,7 163:22 164:15,19 166:17 fetal 22:6 26:3 fetus 26:2,2 fewer 40:12 field 25:17,17 64:19 65:8,11 82:18 83:2 112:10 119:7 134:9 144:4 fields 83:12 FIFRA 1:4,19 4:4 125:5 figure 8:16,18 9:8,9 11:1 12:6,10 14:1 18:7 35:4 93:3 138:21 151:8 161:21 166:16 168:1 figured 21:11 figures 52:21 figuring 88:3 fill 104:4,7,14,16 filled 41:18 filling 137:22 filtration 86:7,14 final 62:9 72:8 90:7	105:15 146:4,4 157:18 171:5,9,12 finally 168:1 find 35:5 36:4 50:17 117:3 132:14,18 161:10 finding 57:21 140:19 fine 116:6 131:21 131:22 151:11,12 finer 118:10 finished 33:22 41:11 45:7 55:17 57:11 59:18 74:14 74:15,19 75:4,5,8 80:7 85:11,14,18 87:4,20 95:3,8,12 124:22 168:7 finite 71:9 first 6:3,17 15:10 31:1 33:5,15 51:18 55:20 56:9 58:22 66:10 74:10 76:6 78:9 79:15 79:20 90:5 94:6 99:19 108:22 114:10 120:12,15 121:1 126:14,17 152:6 158:15 159:22 169:17 fit 18:12 28:16 143:6,10 166:2 fits 116:17 131:5 140:17,17 166:10 166:14 fitting 140:13 141:1,20 142:11 143:19 five 6:13 32:8 59:13 66:20 69:5 71:3 71:19 171:8 five-day 50:3 fixed 133:8 155:12 156:2 flashier 131:10 flexibility 143:3 flip 158:22 159:2
---	--	--	---	---

164:18	four 5:12 8:7 17:22	34:3 35:1,20 39:6	151:20	go 4:19 5:18 6:10
flow 129:21 137:15	24:14 28:10 45:13	40:2 59:2 143:21	GERALD 1:22	7:12 8:14 12:4
148:20 156:15	65:10,13 66:3,5	150:11	getting 43:20 46:20	21:18 31:8 32:22
169:6	66:20 67:2,20	fully 14:4 94:2	55:19 63:15 68:2	34:14 35:14 37:12
flowing 34:6 35:22	69:3,7 71:17,18	fun 25:12	69:20 71:3 82:17	38:13 46:15 47:10
56:4	71:20 108:7 117:9	function 7:1 9:22	101:19 112:20	50:12 55:15 64:7
fluctuation 72:19	118:5 126:14,15	141:12 144:12	113:12 135:10	68:10,15,17 70:3
fluctuations 155:9	141:17 161:21	153:2	140:20 171:18	70:16 77:11 78:4
flux 112:5	fourth 4:11	functional 11:2,13	Gilliom 2:4 41:4	78:17 80:21 84:13
focus 19:14 84:3,9	four-day 17:9,13	functions 145:7	60:6,7 61:12 72:3	103:11 110:16
124:14 162:13,19	17:16,18,21 18:22	FUNGICIDE 1:3	72:4 73:11 76:7	112:10 113:4
focused 17:11	19:3,10,20 22:18	funnel 18:10	87:5 99:16,17	121:3 122:7
focusing 6:20 18:22	25:5 28:6 50:3	further 18:5 23:18	102:22 108:11	123:16 142:9,16
85:14 160:1	67:21 69:10 77:18	36:2 40:14 46:10	113:6,7 114:21,22	142:17,21 143:1
folders 55:15,15	77:20,22 78:13	47:1 93:9 100:15	116:22 123:22	160:8,13 161:5,12
folks 107:17	79:1,3 116:3	124:19 130:12	124:1 132:22	162:12,19,20
follicular 29:4	118:3 132:1,2	138:12 149:11	133:1 145:4,12	163:3 168:12
follow 17:16 104:1	four-node 140:17	future 120:1	149:8,18,19	169:9 171:7
104:8 115:4 124:8	FQPA 2:1 107:5	127:21	153:11 156:6,7	goal 8:21 9:2 90:12
165:12	frame 73:3 90:20	F.L 2:14	gist 5:9	goals 131:8
followed 31:2,2	102:15 137:3		give 4:13 8:16	God 126:20
48:15 119:16	161:3 163:17	G	28:21 29:3 45:17	goes 93:11,12 132:6
139:3	frameworks 13:14	G 1:17,20	82:15 100:17	157:1
following 38:15	Frankenberry 31:3	gamble 84:18	128:19 138:3	going 4:15 5:16,17
77:1 82:9 138:13	63:21 64:6 66:14	gaps 41:18 104:5,7	145:17 153:6	6:2 13:6 14:19,20
139:2	66:18 71:5,16	gathered 166:21	155:10 158:8	18:8 19:19 21:16
follows 34:1 48:11	73:17 143:6	Gaussian 141:20	given 6:19 16:16	26:6 29:13,15
75:5	free 169:6	142:3 143:2	32:4 34:20 38:12	30:4,5,10,15,20
follow-up 58:3	frequencies 126:3	gems 168:10	43:8 50:9 62:1	31:11,19 32:14,15
food 107:5	frequency 1:8 3:10	general 60:8,14	68:14 83:22 89:4	32:19 37:1 39:21
foregoing 84:22	5:21 9:6 14:17	61:7 97:10 103:1	90:2 95:21 96:4	40:9 47:15 50:6,8
172:7	15:2 17:18 19:10	116:9 148:10	100:10 114:13,20	51:10 53:18,20
forever 158:22	19:20 27:16 36:5	generalities 114:12	127:14 131:11	54:5 56:9,19 61:8
forget 33:14 136:11	39:16 40:4,19	generalizations	134:7 138:21	62:22 72:13,21
forgot 66:15	41:1 50:2 78:20	143:2	145:3 148:9	73:13 74:6,16
form 7:13,18 16:3	79:9 81:6 87:13	generally 115:5	155:22 158:21	75:16 76:2 78:12
142:22	88:11 100:11	122:17 138:22	gives 96:18 100:21	79:12,17 81:2
forth 18:2 20:1,5	136:22	generate 60:12	101:18 134:10	82:21 88:4 94:17
26:15 50:12 52:9	frequent 25:6	119:13	135:22 152:19	94:18 101:14
55:6 84:1 101:17	80:19,20 87:15	generated 42:8	giving 32:3 154:2	103:13 104:2,7,8
156:16	97:21	43:2 81:13 115:20	158:19	104:17,18 112:7,9
forward 29:14	frequentist 94:16	generating 164:12	glad 114:9 126:11	112:10,11 115:1
84:14 160:1	frequentist's	generation 170:7	gland 167:19	116:14,15 120:14
171:17	108:14	generator 126:16	gleaned 108:20	120:22 121:2,11
found 51:22 70:7	frequently 81:9	gentlemen 95:6	global 146:19	127:18 128:2,12
92:11,13 143:7	front 28:8	geographic 150:12	globally 103:19	128:15 133:13,15
151:7	full 4:11 5:7 33:7	geostatistical	144:9	133:21 134:2

135:3,18 139:8 140:1 141:4,14 144:2 145:17 150:5 151:14 152:22 157:18 158:18 161:5,11 162:20 164:1,14 164:17 168:19 171:7 good 4:9 75:1 77:21 97:19 100:14,17 108:6 116:5,11 118:11 125:15 132:2,12 140:10 140:20 151:4 152:1,19 153:17 154:2 170:17 gosh 136:14 gotten 67:10 108:6 grab 156:13 graciously 8:3,8 graph 67:18 85:9 graphs 152:20 great 63:15 90:21 92:9 97:13 117:1 148:3 155:21 158:21 162:13 170:20 greater 105:12 155:10 156:1 greatest 90:18 Greenwood 2:5 20:11,13 grid 49:14,17 50:10 52:4 group 14:5 47:2 79:16 124:15 133:18 158:16 171:2 groups 48:6 56:4 161:19 growing 36:15 150:11 guaranteed 142:16 142:20 guess 10:20 18:1 85:4 102:3 133:1	140:8 143:13,15 146:19 149:19 150:2 guidance 92:9 134:10 guideline 162:4 guidelines 162:3 guys 123:21 <hr/> H H 2:2,8 half 5:11 59:19,20 60:4 64:4,4 81:15 half-life 15:19,20 Hamilton 1:15,15 hand 115:14 133:21 169:18 handed 31:9 handle 63:15 handout 35:2,5 36:7 39:20 43:7 43:14 45:4 47:10 53:7 55:21 56:8 59:1,9,10,13 handouts 32:4 64:9 hands 39:9 happen 67:14 76:19 119:7 152:1 happened 55:13 happening 74:20 119:22 120:21 122:5 happens 37:11 68:22 118:9 hard 5:1 54:13 93:1 129:20 171:15 harder 135:1,14 hardest 26:17 57:5 harvest 90:19 havoc 165:20 Hayton 2:6 104:21 104:22 hazard 20:18 21:5 107:7,17 head 170:13 heads 20:14 health 1:6 9:5	29:21 69:1 88:6 123:10 130:17 135:20 137:1,4 161:9 hear 8:11 12:13 164:22 heard 27:22 86:10 100:6 106:10,11 165:22 169:12 heartedly 132:5 heavily 113:12 160:1 Heeringa 1:17,20 45:1,2,2,19,19 46:7,9 58:4,5,13 58:22 70:20,21,21 71:13 82:2,3,3 105:17,18,18 108:7,8 111:10,11 111:11 112:2 154:21,22 Heidelberg 41:15 45:21 48:8 55:19 57:12 65:3 73:19 150:9 hellishly 29:8 help 70:15 77:12 144:18 146:2 148:21 149:3 helpful 10:9 140:22 169:13 helps 78:15 Hendley 31:1,21,22 32:1 33:8 35:7,9 35:14,16 37:16 39:13 40:2,13 42:4,18 43:17 45:9,9 46:3,12,15 46:19 56:2 57:17 57:18 58:12,16 63:8 HERBERT 2:11 herbicide 128:18 herbicides 128:20 132:17 herring 27:18 hesitate 18:9	Hey 85:4 hierarchical 10:1 hierarchy 10:3,5 high 33:17 35:19 67:8 73:9 96:18 97:4,22 101:17 111:5 130:1 133:18 higher 62:14 69:13 74:8 98:19 114:17 143:12 144:22 highest 68:11 71:8 highly 98:2 100:8 144:8 hinging 119:19 histogram 52:2 history 131:12 hit 51:10 79:17,19 79:20,21 108:21 117:20,21 hits 83:17 166:4 hold 39:9 106:20 117:9 158:22 holding 86:5 96:9 96:10 109:20 124:22 HOLLADY 2:7 home 108:21 165:6 Honey 45:22 46:4 48:8 honor 161:1 hope 30:14 64:7 126:11,20 hopefully 4:11 5:11 5:13 52:3 64:13 hoping 64:16 77:12 Horton 2:8 8:3,8 8:12,13 10:21 11:15,16 21:14,21 21:22 22:1 167:3 167:5 Hotel 1:16 hour 5:11 21:15,20 64:4,4 94:14 hourly 111:9 hours 6:9 109:10 house 8:9	HP 27:15,18 HPA 79:15,18 137:3 HPA/HPG 17:8 hugely 28:16 human 1:6 9:5 13:15 26:18 95:5 95:8 96:16 161:9 166:20 170:18 humans 7:8 9:20 19:9,17 23:16,16 28:6,14 96:1 127:16 131:2 human-based 21:13 hundred 29:22 91:22 105:3,3 160:2 hundred-fold 25:16 hydrologist 139:4 hydrologists 32:6 32:10 33:21 94:8 94:10 hydrology 4:21 5:12 30:20 47:2 94:9,19 129:2 130:4 hypothetical 69:1 <hr/> I idea 4:14 8:16 25:17 54:15 94:16 100:21 104:22 151:20 152:1 165:14 166:1 168:5,17 ideas 4:18 94:1 151:2 165:22 identical 48:11 Identification 3:4 identified 41:20 identify 10:8 46:17 101:15 110:3 124:5 151:5 Illinois 56:14 illustrated 45:3
---	---	---	--	---

illustration 72:7 76:16 ILSI 92:6 100:13 image 46:9 impact 17:13,22 30:8 78:12 110:13 implant 165:3 implement 141:5 144:3 implication 150:4 implicit 14:19 importance 60:15 140:9,19 important 13:17 21:4 26:16 28:15 60:10 61:13 90:9 94:13 103:8 117:16,21 129:13 133:11 134:2 138:9 146:12 148:11,16 150:13 151:16 156:8,17 156:20 164:22 impressed 169:22 impression 96:18 138:21 139:5 improve 120:22 154:11 improved 146:1 154:8 improvement 152:16 imputation 138:2 impute 121:11 inadequate 120:20 inappropriate 96:22 incidentally 32:16 include 7:15 included 88:15 149:22 includes 9:1 95:16 121:14 including 89:7 112:4 124:19 inclusion 7:22 increase 110:16	111:6 increased 107:12 135:10 increases 97:7 155:8 increasing 84:18 110:21 independent 93:10 147:14 Indiana 56:14 indicate 9:16 indicated 108:10 indicates 9:4 indirect 100:4 101:6 134:1 individual 30:8 61:2 70:4,16,19 76:12 124:13 131:15 144:3 145:19 152:5 162:21 individually 58:18 146:17 induce 137:4 163:17 infants 9:2 10:17 inference 100:4 117:22 150:15 infestation 128:17 inflated 93:14 influence 77:21 inform 167:1 information 13:16 14:10 82:10 107:10 108:20 114:14 117:18 119:12 121:14 130:14 146:2 149:3,6,10 156:20 156:22 163:14 168:3 170:18 informed 168:3 inherent 92:17 initial 82:21,22 100:17 115:13 139:2 input 84:11 123:17	inputs 146:13 INSECTICIDE 1:3 instance 62:15 106:10 156:18 instantaneous 156:13 157:2 instruction 38:11 instrument 128:1 intake 95:2,4,11,22 96:17 124:21 intakes 96:13 130:9 integrate 16:8 30:9 integrated 15:22 18:21 81:21 89:1 integration 84:10 intend 61:2 intended 21:6 159:16 intense 101:16 102:8,20 103:1 intensify 112:19 intensities 83:6 intensive 6:9 76:3 82:13 97:4 106:14 106:16 153:12 intensively 150:8 157:22 intent 10:15 intention 61:16 interact 9:22 interest 54:21 interested 7:9 50:1 80:2 93:5 interesting 75:17 167:22 169:1,4 intermediate 166:12 internal 15:12,22 17:2 83:18 84:5,6 International 38:2 interpolate 132:4 interpolated 34:18 34:19 36:20 49:12 66:3 115:8,22 interpolates 141:20 interpolating 92:12 136:19	interpolation 36:1 36:18 38:18 41:19 43:2 48:12,18,21 56:21 66:1 70:6 104:12 138:1,17 139:8,16 142:5,7 142:9,18,19,20,22 143:9 151:11 interpolations 65:5 interpret 53:15 78:16 86:3 89:2 160:7,8 164:9 interpretation 23:4 160:15 interpretations 32:13 interpreted 159:6 interpreting 60:10 interquartile 153:14 interspecies 108:1 interval 68:14,16 68:19 69:10,15 70:1 125:22 126:1 127:11,13 135:15 intervals 34:22 36:14 67:22 91:5 97:7 108:15,17 inter-individual 108:2 introduced 14:2 Introduction 3:4 invariant 62:21 investigate 147:20 149:12 invite 14:21 involve 56:20 143:22 involved 13:12 125:8 149:9 involves 141:3 146:13 147:14 in-between 83:18 104:14,16 146:21 160:15 166:5 Iowa 99:9 isolated 165:17	issue 8:1 26:5 62:3 88:10 89:6 94:21 113:9 114:2 125:21 133:22 142:6 144:5 146:12 156:3 158:5 issues 5:21 12:15 14:14 22:17 63:18 113:3 159:6 item 114:2 iterate 131:19 i.e 88:22 <hr/> J J 2:4,15,16,17 JANICE 1:22 January 37:8,10 JEAN 2:14 job 92:2,8 151:1 Joe 4:5 64:10 126:16 170:22 171:12 JOHN 1:21 join 170:16 joined 170:14 Joseph 2:22 3:3 Journal 147:11 July 34:10 37:17 jump 61:2 <hr/> K KANNAN 2:9 Kannan's 165:13 keep 31:4 42:10 55:4 72:13 78:17 93:13 122:15 168:18 keeping 161:2 168:17 keeps 168:9 Ken 10:20 73:7 87:21 102:19 109:5 112:22 120:10 Kenneth 1:17,21 2:3 3:5 KEVIN 2:12
---	---	---	---	---

key 7:15 8:5,6 10:4 12:16 13:3 15:7 15:16 16:22 34:16 36:9 40:7,21 89:20	128:3 130:19,20 130:21 133:2 143:14 144:14 150:17 153:14 154:4 155:17 156:18 157:6 158:6 162:15 163:8 164:13 166:13,15 168:10 168:16,21 169:18	140:2 141:15 largest 129:7 lasso-type 152:18 late 79:14 laugh 66:15 Laughter 6:14 11:21 66:13,17 94:11 109:14 126:22 168:14 169:10	17:4,14 20:18 59:8 70:6 86:13 98:14 123:20 131:13 LH 15:9 17:4,14,22 18:16 23:12 24:15 28:22 29:6 164:6 167:20 life 22:8 161:9 170:11 lifestyle 81:13,20 light 167:17 limit 93:21 126:7 135:15,20 139:20 limited 72:22 limits 106:3 111:2 123:11 Linda 2:17 35:3 58:3 120:12 131:20 152:18 line 77:16,18 78:22 79:3 165:13 linear 12:19 36:17 38:18 41:18 43:1 48:12,18,20 49:12 50:9,15 56:20 61:15 66:1 104:12 138:17 139:7,15 142:19 143:9 linearly 64:20 65:22 lines 46:17 link 19:20,21 47:12 list 126:18 listened 168:16 listening 27:11 literally 162:4 literature 122:14 147:6,14,18,20 liters 105:4 107:21 157:10 litter 24:7 little 4:14 7:3 8:6 13:21 14:19 26:14 47:16 52:2 54:14 59:22 61:4 70:11 74:8 79:20 80:2,3	80:5,13,16 82:15 92:16 93:17 110:7 120:5 121:11 122:1 127:18 128:19 139:9 158:11,19,20 163:8 166:19 170:13 live 69:9 LOC 126:9 127:5 127:14,17 133:5 156:21 located 1:16 LOEL 28:8 long 49:8 53:19 97:8 114:7 117:17 123:12,14 137:9 137:19 151:12 154:18 longer 75:19 77:15 98:18 139:14 longest 152:7 long-term 22:4 128:8 155:7 long-terms 7:16 look 7:12 8:17 12:5 14:9 40:8 45:8,17 53:15 56:9,17 59:14 65:9 67:19 68:4,16 69:11,17 70:12 74:3 75:18 78:19 82:4 86:2 88:1 97:13 99:7 107:1 120:4 123:3 129:6 134:8,13 144:15 145:6 147:16 171:16 looked 24:2 34:5,7 42:9 50:2,5 58:18 59:1 67:6,7 68:8 71:7 113:3 120:10 123:2 126:20 148:19 153:15,16 154:4,12 looking 11:7,8,8 30:3,11 45:15 50:20 54:2 60:20
kind 4:14,16 17:12 17:19 27:5 29:14 29:15 30:4,18 31:4,15,20 44:11 53:17,19 68:16,18 69:19 73:6 77:12 79:6 99:8 100:12 100:18 106:18 109:3 110:20 115:1 120:14 121:1,4,12,14 122:4,6 123:15 128:20 132:20 134:4,17 135:22 151:2 153:5,6,7 153:20 154:10 165:10 168:1,18	knowing 54:12 77:15 78:14 91:7 knowledge 118:14 146:7 known 88:16 124:5 knows 119:8 kriging 70:15 141:12,19 142:21 143:7,20 144:5,11 151:19 Krishnan 2:9 6:2 14:13,15 21:2,7 22:9 24:10,11 30:14 83:14,15 165:7 Krishnan's 167:8 K.H 2:11	Laura 170:22 laws 146:8 layer 123:7 lead 17:17 138:5 156:1 leads 135:16 141:16 learn 103:18 learned 169:21 leave 59:10 116:10 116:18 127:9 136:5 171:6 LeBLANC 1:22 led 35:1 167:21 Lee 2:11 52:17,18 53:1 58:3 103:3,4 117:5,6 134:19,20 137:18,19 148:1,4 149:20 150:22 154:9 left 32:16 156:22 162:17 length 49:11 lengthy 162:10 let's 65:9 68:10 77:11 90:12 125:18 137:20 143:4 169:9 level 9:15 19:5 29:21 30:3 70:16 70:19 85:10 107:20 118:1 121:21 123:18 126:7 131:1 135:1 145:19 148:13 166:1 levels 10:3,6 15:9	life 22:8 161:9 170:11 lifestyle 81:13,20 light 167:17 limit 93:21 126:7 135:15,20 139:20 limited 72:22 limits 106:3 111:2 123:11 Linda 2:17 35:3 58:3 120:12 131:20 152:18 line 77:16,18 78:22 79:3 165:13 linear 12:19 36:17 38:18 41:18 43:1 48:12,18,20 49:12 50:9,15 56:20 61:15 66:1 104:12 138:17 139:7,15 142:19 143:9 linearly 64:20 65:22 lines 46:17 link 19:20,21 47:12 list 126:18 listened 168:16 listening 27:11 literally 162:4 literature 122:14 147:6,14,18,20 liters 105:4 107:21 157:10 litter 24:7 little 4:14 7:3 8:6 13:21 14:19 26:14 47:16 52:2 54:14 59:22 61:4 70:11 74:8 79:20 80:2,3	live 69:9 LOC 126:9 127:5 127:14,17 133:5 156:21 located 1:16 LOEL 28:8 long 49:8 53:19 97:8 114:7 117:17 123:12,14 137:9 137:19 151:12 154:18 longer 75:19 77:15 98:18 139:14 longest 152:7 long-term 22:4 128:8 155:7 long-terms 7:16 look 7:12 8:17 12:5 14:9 40:8 45:8,17 53:15 56:9,17 59:14 65:9 67:19 68:4,16 69:11,17 70:12 74:3 75:18 78:19 82:4 86:2 88:1 97:13 99:7 107:1 120:4 123:3 129:6 134:8,13 144:15 145:6 147:16 171:16 looked 24:2 34:5,7 42:9 50:2,5 58:18 59:1 67:6,7 68:8 71:7 113:3 120:10 123:2 126:20 148:19 153:15,16 154:4,12 looking 11:7,8,8 30:3,11 45:15 50:20 54:2 60:20
kinds 132:17 163:12 164:7 knew 122:13 knocking 86:13 know 5:17 8:13 11:6 12:2 14:8 15:1 17:21 19:5 20:8 23:20 28:18 29:7,10,22 30:7 30:16 31:18 49:17 51:5,9 56:15 57:5 57:10 59:1 60:1 63:22 74:20 76:14 81:12 82:12,14 90:20 91:2,9 102:15 103:11 108:9 110:2 111:8 111:20 117:15 120:11,19 121:6 121:22 123:18,20 123:21 127:21	knowing 54:12 77:15 78:14 91:7 knowledge 118:14 146:7 known 88:16 124:5 knows 119:8 kriging 70:15 141:12,19 142:21 143:7,20 144:5,11 151:19 Krishnan 2:9 6:2 14:13,15 21:2,7 22:9 24:10,11 30:14 83:14,15 165:7 Krishnan's 167:8 K.H 2:11 <hr/> L <hr/> L 2:6 lab 80:9 laboratory 113:22 166:21 lack 8:1 lag 109:8 110:17 Lake 41:6 lamppost 168:2 landscape 129:18 large 28:21 29:3 41:8 91:20 109:19 109:20 130:3 161:3 162:18 largely 32:22 larger 71:6 75:19 96:10,17 99:5 114:17 130:7 131:7,16 138:3	140:2 141:15 largest 129:7 lasso-type 152:18 late 79:14 laugh 66:15 Laughter 6:14 11:21 66:13,17 94:11 109:14 126:22 168:14 169:10 Laura 170:22 laws 146:8 layer 123:7 lead 17:17 138:5 156:1 leads 135:16 141:16 learn 103:18 learned 169:21 leave 59:10 116:10 116:18 127:9 136:5 171:6 LeBLANC 1:22 led 35:1 167:21 Lee 2:11 52:17,18 53:1 58:3 103:3,4 117:5,6 134:19,20 137:18,19 148:1,4 149:20 150:22 154:9 left 32:16 156:22 162:17 length 49:11 lengthy 162:10 let's 65:9 68:10 77:11 90:12 125:18 137:20 143:4 169:9 level 9:15 19:5 29:21 30:3 70:16 70:19 85:10 107:20 118:1 121:21 123:18 126:7 131:1 135:1 145:19 148:13 166:1 levels 10:3,6 15:9	17:4,14 20:18 59:8 70:6 86:13 98:14 123:20 131:13 LH 15:9 17:4,14,22 18:16 23:12 24:15 28:22 29:6 164:6 167:20 life 22:8 161:9 170:11 lifestyle 81:13,20 light 167:17 limit 93:21 126:7 135:15,20 139:20 limited 72:22 limits 106:3 111:2 123:11 Linda 2:17 35:3 58:3 120:12 131:20 152:18 line 77:16,18 78:22 79:3 165:13 linear 12:19 36:17 38:18 41:18 43:1 48:12,18,20 49:12 50:9,15 56:20 61:15 66:1 104:12 138:17 139:7,15 142:19 143:9 linearly 64:20 65:22 lines 46:17 link 19:20,21 47:12 list 126:18 listened 168:16 listening 27:11 literally 162:4 literature 122:14 147:6,14,18,20 liters 105:4 107:21 157:10 litter 24:7 little 4:14 7:3 8:6 13:21 14:19 26:14 47:16 52:2 54:14 59:22 61:4 70:11 74:8 79:20 80:2,3	80:5,13,16 82:15 92:16 93:17 110:7 120:5 121:11 122:1 127:18 128:19 139:9 158:11,19,20 163:8 166:19 170:13 live 69:9 LOC 126:9 127:5 127:14,17 133:5 156:21 located 1:16 LOEL 28:8 long 49:8 53:19 97:8 114:7 117:17 123:12,14 137:9 137:19 151:12 154:18 longer 75:19 77:15 98:18 139:14 longest 152:7 long-term 22:4 128:8 155:7 long-terms 7:16 look 7:12 8:17 12:5 14:9 40:8 45:8,17 53:15 56:9,17 59:14 65:9 67:19 68:4,16 69:11,17 70:12 74:3 75:18 78:19 82:4 86:2 88:1 97:13 99:7 107:1 120:4 123:3 129:6 134:8,13 144:15 145:6 147:16 171:16 looked 24:2 34:5,7 42:9 50:2,5 58:18 59:1 67:6,7 68:8 71:7 113:3 120:10 123:2 126:20 148:19 153:15,16 154:4,12 looking 11:7,8,8 30:3,11 45:15 50:20 54:2 60:20

62:20 67:11,19 69:2 70:1 75:12 76:2,9,14 77:14 77:18 79:6 80:21 81:3,19 86:21 94:3 103:9 106:12 106:13,17 145:12 145:15,16 146:8 147:17 149:4 154:14 156:12 163:14 164:2,10 167:17 looks 107:10 126:14 136:12 147:12 lose 57:2 156:4 lost 35:8 lot 6:10 11:10 20:16,19 21:8 25:22 31:13 56:18 61:1 64:8 70:8 83:9 100:6 103:18 107:22 111:20 115:1 120:14 124:7 128:12 130:14 132:12 135:14 142:7 143:8,14 145:14 145:20,21 154:16 158:1 160:7,22 166:4,4 167:20,21 169:17 lots 169:19 Louis 44:15 48:2 low 45:10 52:8 67:8 98:7,11,14,17 lower 62:15 68:12 162:15 lowest 57:4,6,14 68:13 69:6,12,17 71:7 Lowit 107:2,2 158:6,7 163:5,20 164:13,16,21 168:15 169:3,11	M 1:17,21 magenta 75:2 76:19 magnitude 54:13 67:14 70:12 78:8 105:11 main 26:13 34:2 maintenance 95:19 major 11:4 153:18 159:22 making 11:10 27:15 87:1 118:8 154:9 163:8 mammary 12:6 167:19 man 64:3 managed 153:19 manager 109:10 110:5 managers 165:20 march 37:11 50:13 Marry 143:6 Mary 31:3 63:21 64:1 mass 27:20 masses 12:20 massive 85:20 master's 24:1 match 146:15 170:19,19 matches 153:7 material 31:13 materials 132:17 maternal 25:22 matter 95:17 131:2 139:10 maturation 24:17 Maumee 48:9 max 50:18,18,19,19 50:22,22 51:7,14 51:15,20,21 52:7 52:7,13 60:1 61:17 62:20,21 67:12 68:12 109:16 maxes 51:6 maxima 145:13,16	146:10 maximum 36:21 38:21 39:2,2,4,5 42:9,11 44:1,5,6 44:10 45:10 53:21 66:8,21,22 67:3,7 67:10,21 68:9 138:5,6 139:11,12 139:22 140:15 142:1 143:11,18 144:18,19 149:4 ma'am 110:2 MCL 98:8 mean 18:6 19:21 21:1 27:22 43:9 44:11 59:22 63:3 69:4 74:12 82:16 83:17 85:18 93:12 102:21 108:12 111:7 121:3,19,21 123:9,14 125:7 135:12 161:11,13 means 57:8 150:14 161:20 meant 72:7,9 87:18 measure 15:22 83:18,20 84:5,6 103:11 140:22 168:8 measured 15:8 16:14 41:17 76:11 76:12 measurement 77:17 102:21 103:10,19 119:5 142:12 measurements 17:1 34:21 77:22 117:4 133:19 138:1 measures 108:16 165:2 measuring 168:7 mechanism 29:19 mechanisms 22:12 median 54:3 109:13,16	meet 102:16 meeting 3:2 4:5 5:9 5:14 8:20 14:2,3 136:5 158:15,16 171:8,16,21 172:5 172:7 meetings 169:18 170:1 Melanie 110:4 member 157:19 members 1:19 2:1 3:5 4:22 MENDEZ 10:11,14 mention 140:7 147:2 155:2 mentioned 15:16 41:10 44:14 56:2 101:2 120:12 129:5 132:7,11 146:5 147:3,8 148:11 153:11 mentions 141:10 Mercifully 157:15 merits 114:16 136:16 message 165:3 metabolite 15:5 16:12 metabolites 7:18 15:11,21 16:3 method 117:1 127:20 134:1,8,14 138:11,14,19 140:2,4 142:22 146:4,5 168:13 methodology 40:8 40:11 110:18 111:1,5 120:12 121:2,18 123:11 152:13 153:20 methods 70:14 88:11,15 92:18 93:4,16 101:11 114:10,19 115:3 124:11 136:21 137:11,22 138:2 139:7,16 141:14	141:17 142:18 147:12 148:9 151:10,11 metric 84:12 metrics 26:18 mice 25:15,17 microgram 105:4 micrograms 105:4 microphone 31:2 163:16 middle 47:12 54:19 153:18 164:6 mike 4:7 miles 46:6 milligrams 28:9 million 29:22 millions 160:9,9 161:12,12,12 min 109:16 mind 17:5 20:9 28:20 34:17 78:17 98:4 164:1 mindful 7:16,17 minds 33:21 mini 163:12 minimum 67:7 91:21 118:5 minor 154:22 156:3 minus 68:6,15,18 71:20,22 minute 84:17 165:2 171:8 minutes 6:13 8:17 31:5 148:4 misinterpreted 25:9 misinterpreting 85:15 misleading 96:18 misread 25:9 missing 47:11 53:5 72:18 78:11 138:12 139:10,12 140:15 Mississippi 128:13 Missouri 41:12
M				

44:2 45:7,10 48:4 56:22 75:21 99:7 99:10 mixed 12:22 34:6 56:4 MOA 8:19 12:6 13:13,15 14:1,11 18:7,10,11 164:11 MOAs 13:17 mode 7:4,6 8:7 9:9 9:10,12 26:7 163:10 167:18 model 26:16 28:14 73:8 84:11 96:11 101:2 104:4,6,11 104:12,14,17 112:3 118:12,16 124:2 132:4 134:1 137:7 140:21 141:20 143:20 144:1 145:5,7 151:5,18 modeling 48:20 104:10 117:8 119:12,15 121:3,9 121:14,17 136:17 137:16 147:6,13 models 97:9 101:13 118:7 124:4 141:12,13,13 143:7 144:12 145:11 146:1,1,6 147:3 154:10 moderate 137:9 modes 140:10 modified 9:10 molecules 122:3 Monday 31:15 49:19,20 50:12,14 51:3 140:8 Mondays 50:11 51:9 money 21:8 128:12 monitored 150:8 monitoring 1:7 3:10 5:22 14:17 15:2 16:20 17:18	21:12 25:6 29:18 30:4 36:13 37:7 40:22 62:3 76:10 87:12 88:21 89:14 89:20 99:22 102:11 106:12,21 110:9,10 125:7,8 126:3,7 156:9 157:1 160:4 monotonic 155:7 155:22 month 53:17 monthly 50:5 months 109:10 136:11 161:21 166:13 morning 4:9,15 31:7,18 64:10 115:5 135:11 165:22 Mosquin 33:18 43:8,16 47:17 Mosquin's 43:14 mothers 24:3 mountains 162:7,9 move 29:14 33:14 86:8 93:8 99:5 114:7 125:18 127:18 129:15 141:22 168:2 moved 38:9 128:15 129:18 moving 78:8 86:6 91:9 111:8 127:16 134:10 multi 48:1 multiple 12:20,20 99:6,7 101:3 112:3 167:12 multiplier 44:6 multipliers 44:3 multi-part 8:18 9:9 multi-year 48:6 58:19 multi-years 49:13 muted 78:11 M.D 2:16	<hr/> N <hr/> nailed 159:4 name 63:22 names 126:19 narrow 16:19 68:7 152:4 nature 88:1 89:4 120:13 133:5 near 35:11 41:13 41:14,17 nearly 48:15,16 Nebraska 99:10 necessarily 24:9 61:17 83:19 86:15 87:2 103:17 141:6 142:9,17 143:3 necessary 27:7 88:12 131:6 need 5:7 9:4 10:9 27:6 32:7 34:14 39:9 80:20 91:19 91:22 93:15 94:7 98:5 100:21 101:16 102:8,15 104:6,10,13,13,15 105:7 107:17 117:2,3 120:1 122:5 124:6 130:20 131:8,20 132:5 141:1,7 144:6 146:16 157:6,9 165:9 needed 78:4,5,6 124:19 130:19,20 131:10 137:3 163:17 needs 103:14 117:19 Neither 138:2 Nelson 63:21 73:22 82:4 107:9 159:12 nervous 11:12 network 105:6 140:5 141:3 142:4 142:14 154:4,6 networks 26:6 neural 140:5 141:3	142:4,14 neuro 154:4,5 neuroendocrinol... 11:18 never 21:16 41:9 132:14,18 141:14 new 8:9,15 9:4 10:8 22:2 27:14 51:16 65:20 66:2 70:2 128:10 147:18 158:5 159:10,14 161:8,18,18 162:14 163:14 168:3 newly 9:11 news 97:19 nice 5:5 29:19 30:7 92:8 151:1 153:13 154:10,15 night 66:15 74:21 85:9 158:14 165:6 169:1 nine 37:20 40:10 158:12 NOAEL 19:6 nodes 140:12,20 noisy 142:4 non 91:13 non-expert 141:5 non-parametric 91:10 120:13 non-parametrica... 149:5 non-sampling 144:20,21 non-stationary 143:22 normal 153:13 normally 93:10 156:12 noted 118:20 notice 55:1,7 57:3 152:20 noticeable 154:14 NRDC 132:14 nth 155:5 nuance 163:10	number 13:13 31:9 32:18,20 37:3 40:17 49:6 51:14 57:4,7,14 59:14 60:11 65:14 67:19 68:4,17 71:6 83:9 95:13 99:12 109:8 117:9 122:12 126:16 127:17 140:20 141:10 145:1,11 158:11 163:19 164:6,7,8 164:12 numbers 19:19 51:8,13,18,19,21 51:22 55:2 57:3,6 60:11,12 110:11 134:18 164:2 numerical 40:1 59:2 114:16 NU-MAY 2:13 N.W 1:16 <hr/> O <hr/> objective 60:16 61:9 102:13 103:2 113:15 115:20 124:6,8 150:17 157:6 objectives 116:12 134:6 observation 155:1 observations 16:16 91:19 94:19 observe 146:11 observed 138:4 140:3 141:16 142:10 143:12 146:15,22 obtained 34:22 38:22 43:4 obvious 19:18,20 19:21 24:19 102:6 Obviously 51:10 59:21 occur 10:4 22:5 71:14 118:2 138:6
--	---	---	---	---

<p>occurred 144:20 occurrence 60:20 89:5 137:8 occurring 22:10 occurs 142:2 October 169:2 offer 116:22 offered 8:3,8 office 125:11 158:16,17 159:20 Official 2:22 4:6 Oh 54:4 55:13 109:18 136:14 163:22 172:2 Ohio 44:16 56:14 75:2 76:14,15 okay 4:3 8:15 21:4 31:22 33:5,15 35:3,7,9,13 36:2,6 37:16 40:15,16 42:17 53:1,4 54:5 54:9 57:10 60:5 77:11 78:4 79:17 85:5 88:8 90:13 91:22 98:12 106:8 108:6 114:6,22 125:13 134:10,12 136:3,12,14 144:11 148:6 157:12 163:22 164:15 167:5 old 160:5 161:5 once 19:5 44:8 53:17 81:5 110:15 116:11 124:8,13 133:8 151:7,19 152:6 171:5 once-a-week 43:22 ones 41:22 52:18 68:17 100:20 115:16 131:17 143:12 one-day 52:14 53:8 79:16 one-pager 33:1 one-time 24:3 one-year 138:1</p>	<p>open 6:4 104:20 157:18 158:1 Opening 3:2 operators 38:12 95:18 opinion 27:17 opportunity 32:3 opposed 130:16 options 92:8 oral 15:18 19:8 orange 54:18,19 order 45:13 91:13 92:1 109:19 orders 105:11 organic 95:16 organisms 9:20 organization 10:1 organizing 14:10 original 50:18 51:1 153:9 outcome 16:14 17:3 18:4,17 24:16 25:2 outcomes 18:11 22:5 outlining 92:8 outside 141:22 142:2 143:11 out-of-sample 146:2 ova 23:19,19 overall 16:17 43:22 51:7 106:22 125:3 153:19 overestimate 70:9 92:14 138:15,16 138:18 overestimated 70:8 overestimation 139:18 overlaid 49:14 overlay 50:9 overlying 165:15 Overleaf 37:5 overviews 160:12 overwhelmed 122:3</p>	<p>over-fitting 140:10 ovulate 23:15 ovulation 23:13,15 23:19 O'Bryne 14:21 105:8 O'Byrne 2:12 27:10,11 85:6,7 105:9 165:8</p> <hr/> <p style="text-align: center;">P</p> <hr/> <p>package 35:12 page 59:13,13 97:13 pages 31:9 32:22 43:15 97:18 160:9 161:13,16,16 162:11 169:19 panel 1:4,15 3:5,6,8 4:4,13,17,22 6:4 8:19 10:15 31:10 32:2,7 34:17 47:8 68:21 88:20 104:20 152:10 157:18,19 169:9 169:17 170:16 171:5,15 panelists 76:7 paper 23:8,8 39:10 41:8 65:22 73:18 88:10 89:7 97:14 100:13 115:6 125:21 131:7 140:18 142:8 145:4 146:5 147:4 147:10 154:3 162:7,9 papers 171:7 PAPK 26:16,19,19 parameter 129:7 parameters 129:9 146:14 parametric 91:14 paraphrase 127:2 parent 15:19 16:11 part 6:18 14:15 16:20,21 47:10</p>	<p>58:22 86:19 99:19 101:13 102:1 106:22 125:3 127:2,4 129:16 133:14 134:2 136:13,14 139:10 148:7,17 156:13 159:21 162:14,19 particular 7:8 16:6 16:11 75:10 90:10 90:15,15 100:10 100:19 119:20 136:20 145:21 163:9 particularly 15:16 72:9 82:5 101:12 137:2 141:18 165:7 particulars 127:10 partition 56:8 parts 62:16 97:16 105:3 130:10 148:7 pass 169:1 pathway 26:7 pathways 12:18 pattern 15:13 75:5 75:20,22 76:19 77:1,8 82:4 patterns 87:7,8 89:5 114:13 137:15,16 148:20 148:21 166:6 Paul 31:22 35:3 45:3,9 46:8 57:18 62:8 pay 136:7 154:18 PBPK 84:11 PD 14:20 peak 26:22 41:20 42:11 43:3,9 45:16 75:19,19 82:4 90:4 122:4 138:9 139:2,4,18 140:14 144:22 145:8 peaks 45:12 99:4,6</p>	<p>99:8 105:7 110:22 117:16,17 143:16 153:8 PENELOPE 2:4 Penny 160:19 164:16 169:7 people 21:8 46:9 61:21 69:1 73:16 77:13 81:21 98:17 98:22 103:12 112:8 124:16 126:15 155:2 167:7 170:2,16 171:3 pep 158:19,20 percent 44:2,2,2,11 47:19 52:12,16 53:19,20 54:6,8 55:6 57:7,8,9,15 63:4,5,6 68:2,6 69:5,7,12,14,17 69:18 71:7,8 97:15 127:11,12 134:12 154:12 percentage 43:10 percentile 42:7 53:13 54:3,5 59:17 60:2 67:8 90:11 percentiles 42:3,15 51:22 53:6 67:8,9 perfect 53:9 54:17 performance 44:20 44:21 53:3 55:12 62:4 68:3 69:5,16 69:19 88:17 performed 160:11 period 16:6,12 18:22 21:15 23:10 37:13 78:13,14 81:7 82:18 83:1 86:5 90:11,17 97:5 periodic 105:22 periodicity 89:8 108:19 155:4 periods 46:17 83:8</p>
---	---	---	--	---

88:18 97:22 98:18 98:19 Peripherally 170:12 permanence 112:6 permanent 169:17 Perry 41:6 persistence 111:22 person 158:18 personal 79:18 160:16 171:1 personally 121:5 perspective 108:14 160:16 pertinent 27:4 perturbed 155:12 156:2 pesticide 88:13,16 89:5,11 136:19 137:15 139:3 145:3 148:21 pesticides 159:20 160:22 pH 95:17 pharmacokinetic 15:15 pharmacokinetics 16:18 phase 29:5 phrased 24:12 physical 146:7,9 physiological 19:22 20:4 22:12 physiologically 30:12 physiologists 31:19 physiology 28:16 Ph.D 1:17,17,20,21 1:21,22,22,23 2:2 2:2,3,4,4,5,6,7,8,9 2:11,12,13,14,15 2:16,17 pick 115:16 160:13 picked 80:6 picking 111:9 136:6 144:14 picture 49:16 54:14	154:2,12 pictures 55:2 piece 38:1 39:8 pieces 9:17 39:10 149:3,9 pile 66:11,20 74:7 PK 5:20 14:14,18 14:20 15:6 place 76:6 96:15 135:5 placing 126:5,8 134:22 plan 38:12 53:3 55:11,17 58:11 planning 82:12,21 130:12 plans 4:14 73:21 100:16 112:18 plant 95:14,18 96:8 96:16 112:9 113:20 planted 112:4 128:11 planting 90:19 players 153:17 playing 134:9 Plaza 1:15 please 10:12 25:4 81:2 89:15 110:3 114:14,18 126:4 136:16 137:6,10 pleased 12:13 plethora 132:16 plucked 85:9 plus 16:3 160:2 167:9 point 5:4,13 10:4 12:16 19:9 29:16 30:1,2,21,22 38:4 41:20 60:8,14,21 61:7,14,16 62:11 72:6,14 78:8 81:12,19 82:20 87:1,16 88:6,22 94:13 96:5 100:3 102:4,6 103:22 113:13 116:9	120:6 122:10 123:1,8 124:13,18 125:1 132:2,10,11 148:16 150:2,16 154:1,9 155:20 157:7,22 158:12 159:9,11 163:7 164:22 167:1 169:11 171:11 pointed 63:11 points 9:1 19:1 33:19 34:3,4,13 34:17 36:1,9 38:18 40:21 43:2 51:5 57:22 62:16 79:4 103:6 124:7 136:20 142:10,13 142:16,18,21 143:1 152:14 161:7,14 170:9 polyploidy 23:22 polyspermia 23:22 pond 96:9,10,17 pool 85:19,19 pooling 144:10 population 10:18 29:21 30:9 34:21 69:21 70:18 128:16 Portier 1:17,21 3:5 4:7,9 6:15 10:13 10:19,20 11:22 12:8 13:10 14:12 20:11 21:22 22:14 23:6 24:10 25:10 27:10 29:12 33:6 37:14 40:6 43:19 44:19 46:8,14,16 49:1 53:14 54:2,7 54:10 58:2 60:5 62:8 63:20 70:20 72:2 73:7,8,15 74:2 79:13 81:11 83:14 84:16 85:3 87:21,22 89:17 94:4,12 99:15 102:19,20 103:3	104:19 105:8,13 107:15 108:5 109:3,5,12,15,22 110:12 111:14,16 112:22 113:1 114:4,21 116:20 117:5,10 120:8,10 123:9 125:13,18 126:13 132:22 134:19 135:7,9 136:4,8 137:18 149:13,18 150:21 152:9 156:5 157:8 157:16 163:1 167:2 168:4,9,15 169:8 171:4 172:4 poses 130:17 position 124:3 positive 93:13 possibilities 61:8 possibility 26:22 164:9 possible 7:6 51:5 52:20 63:14 70:11 106:20 113:17 146:14 148:19 post 167:17 post-emergent 82:7 post-peak 139:19 potential 14:1 35:17 89:2 139:12 141:11 145:14,20 145:22 potentially 78:11 133:18 140:13 power 77:10 powerful 149:6 ppb 131:3,3 practical 111:2 114:15 141:6 practice 161:20 precise 103:15 precisely 40:13,13 116:13,13 precision 91:17 131:8,11 preclude 26:22	precursor 15:7 17:1 18:14 162:16 precursors 15:8 16:14 17:14 19:7 24:14 predict 112:7,8 140:2 141:15 145:13 predictable 133:12 predicted 138:3 predicting 145:6 146:10 prediction 69:22 126:1 140:11 predictions 101:6 145:8 146:3,15,21 prefer 21:20 pregnant 24:4 preparation 8:20 preparing 13:5 presence 92:19 130:5 present 1:19 2:1,20 93:7 118:17 158:5 171:22 presentation 31:6 31:14 32:20 33:16 36:4 39:14 40:16 40:18 47:4 158:15 presentations 4:19 5:10 171:19 presented 31:12,17 35:11 65:22 88:9 114:10 presiding 1:18 presume 163:19 pretty 13:18 23:12 56:4 72:21 74:22 77:21 82:11 89:21 91:9 97:17 125:15 135:21 149:16 150:6 157:22 165:4 previous 8:2 79:5 pre-emergent 82:7 pre-emergent/po... 82:11
---	---	---	---	---

<p>primarily 5:20 6:5 58:16</p> <p>primary 58:13 120:6</p> <p>principle 121:1</p> <p>principles 120:15</p> <p>prior 90:19</p> <p>probability 38:6 124:5 133:18,22 134:7,15 135:10 135:18</p> <p>probably 12:19 30:3 31:5,6 34:14 53:4 60:8 78:3 79:17 87:22 97:5 98:4,11,13,16 100:5 102:6 103:13 108:4 109:18 110:19 112:6 115:11 116:13 117:8,11 122:6 127:17 131:15 135:14,19 139:8,10 150:3 151:8 154:13 155:2 156:3 158:12 159:6 160:14</p> <p>problem 45:20 60:19 91:6 93:2,9 108:13 111:18 115:14 124:18 134:22 135:1 146:18</p> <p>problems 101:17 153:19</p> <p>procedure 39:21 47:15,17,18,22 48:10 56:1 148:8</p> <p>Procedures 3:2</p> <p>proceeding 84:22</p> <p>process 34:2,11 36:8 71:15 72:8 95:20 109:7,9 113:18 116:6,17 119:15 120:17 122:21 125:4</p>	<p>133:6 141:20 142:3 146:8,9 147:13 154:8,17 155:3 156:4 171:8</p> <p>processed 31:10 32:12 39:8 80:8</p> <p>processes 74:15 123:19 143:2 147:16</p> <p>processing 43:12</p> <p>produce 69:22 171:9</p> <p>productive 20:7 108:4</p> <p>products 84:2</p> <p>proestrus 23:11</p> <p>profile 15:3 16:13 16:17 36:19,20 38:19 43:3 44:9 44:20 48:2 49:12 49:19 50:9,13,15 50:19,19 51:1,7,8 51:15,21 52:14 58:19 61:15 62:6 64:21 65:7 79:1,4 85:11,17 86:22 111:17 152:22 153:1,9</p> <p>profiles 44:22 49:8 49:9,10,10,11 50:5 54:21 59:11 84:12</p> <p>program 36:14 41:1,14 62:3 65:12 97:11 110:10 130:18,21</p> <p>programming 22:4</p> <p>programs 41:15</p> <p>projection 105:21</p> <p>promise 141:17</p> <p>promised 31:4</p> <p>properly 32:11 85:12</p> <p>properties 91:4</p> <p>proportion 101:15 108:15 125:2 129:11</p>	<p>proportional 139:3</p> <p>proposal 161:18,18</p> <p>proposed 137:11 151:11</p> <p>protect 19:12,17 21:9</p> <p>protection 1:1 107:5</p> <p>protective 20:17 88:4</p> <p>protocol 37:7</p> <p>provide 92:9</p> <p>provided 39:20</p> <p>provision 107:6</p> <p>pubertal 164:5</p> <p>public 5:8,9,14 29:21 66:16 86:11 88:6 93:6 123:10 135:16,20 153:15 171:21</p> <p>published 23:8 122:14</p> <p>pull 46:21 151:2</p> <p>pulled 76:5 171:18</p> <p>pulling 74:21 151:3</p> <p>pulse 81:18</p> <p>pumps 96:9</p> <p>purpose 65:19 71:6</p> <p>pursued 163:13</p> <p>pursuing 114:16</p> <p>pushing 92:21 162:17</p> <p>put 14:6 29:14 31:11 43:15 49:17 54:13 55:2,21 78:17 90:5 92:5 107:19 123:11 131:20 133:3,4,13 135:15 147:21 148:1 151:18 167:14</p> <p>putting 133:6 135:2 151:22 160:22 167:13</p> <p>P-R-O-C-E-E-D-... 4:1</p> <p>p.m 172:6</p>	<p>Q</p> <p>qualities 84:15</p> <p>quality 107:5</p> <p>quantile 90:2,10,10 91:18</p> <p>quantiles 91:17 92:15,15 145:13</p> <p>quantitation 89:10</p> <p>quantitative 101:19</p> <p>quarter 52:12 55:5</p> <p>quarterly 125:9</p> <p>question 3:7,8,13 3:15,17,19 4:15 5:18 14:16 17:20 24:13,19,21 30:11 30:17 34:16 59:7 62:10 68:11 85:5 85:8 88:7 90:14 96:22 99:19 102:2 105:19 109:4 114:8 117:14 120:13 133:2 135:22 136:3,13 148:7,17 157:14 163:15 164:17 166:15</p> <p>questioned 18:18</p> <p>questions 5:1,11,13 5:19 31:8 33:2,20 36:2 40:14 47:2 58:3 60:9,16 67:16 68:20 74:3 79:11 85:4 113:9 125:14 126:15,19 165:11,17</p> <p>quick 23:12 31:15 113:18 150:6</p> <p>quicker 40:20</p> <p>quickly 64:7</p> <p>quite 28:15 35:8 45:11,11 55:10 61:21 73:19 89:22 145:18</p>	<p>R</p> <p>R 1:21</p>	<p>rainfall 82:20 83:6 111:21 112:8,12 128:8 130:11</p> <p>raining 99:9,10,10</p> <p>rains 83:12</p> <p>rainy 82:18 83:1</p> <p>raised 24:12,21 59:7 76:7</p> <p>ramify 10:6</p> <p>ran 65:21</p> <p>random 38:8,10 58:10 71:2 82:9 92:18 126:16 131:5 141:12 144:12</p> <p>randomly 155:11 156:1</p> <p>range 67:6 68:3,7 100:3 150:7,12 153:14</p> <p>ranged 52:7</p> <p>rat 19:6,11,12,15 21:4 23:16 28:6 28:14,21</p> <p>rate 15:17 42:15 82:9 83:22 110:16</p> <p>rating 84:8</p> <p>ratio 45:16,17 51:14 52:13 54:18 62:21</p> <p>ratios 52:4,6 62:20</p> <p>rats 17:8 21:9 23:16,16 25:15,17 26:18</p> <p>raw 36:10 62:14,15 63:14 74:17 75:2 75:6,10 85:12 123:11,12,17 168:7,8</p> <p>reach 121:21 131:8</p> <p>reached 55:13 80:8 163:11</p> <p>read 36:11 49:2 54:10,13,14 113:4 136:13</p> <p>reading 85:4 109:4</p> <p>real 44:7 97:5</p>
---	--	---	--	--------------------------------------	---

115:18 117:14 119:21 153:1 realistic 148:13 151:15 realistically 98:16 reality 61:19,20,21 62:1,2 65:2,8 92:1 115:14 119:3 realization 119:16 119:20 realizations 119:17 realize 32:7 39:9 41:9 78:4 realizes 116:4 really 5:2 6:5 7:11 12:13 21:12 29:20 30:17 31:16 33:12 45:18 48:13 55:10 56:12 62:3 78:15 101:3 104:3 109:12 111:8 112:1 113:8,15,17 117:6,15,17,19 120:20 127:13 128:3 129:1 132:4 133:11 143:13 144:17 146:9 147:17 148:18,18 148:21 149:3 150:11 151:4 152:12 154:2,8,14 154:16 157:3 165:9 170:1,2,11 reason 24:21 30:15 31:16 38:10 76:5 87:18 92:16 133:14 reasonable 118:18 119:11 reasonably 139:17 reasons 18:6 83:9 recap 128:20 receive 65:16 received 109:9 recognize 9:19 123:10,14 155:2 recommend 144:9	recommendations 113:2 reconsider 9:6 27:15 reconsideration 160:3 record 5:8 50:14 66:16 85:1 163:6 recorded 34:9 39:4 51:13 recording 53:12 records 162:1 recreating 72:21 recurring 73:6 red 27:18 46:16 77:17 78:22 reduce 94:1 reduced 24:6 40:8 84:19 107:8 Reed 2:13 6:1,11 6:12,17 25:10,11 30:14 107:15,19 reevaluate 10:16 reevaluation 1:6 4:5 159:21 refer 163:20 reference 64:21 referenced 92:6 references 148:2 149:21 referred 22:9 94:8 115:3 referring 32:15 43:14 refers 33:5,15 36:3 40:17 163:18 refine 93:4 refinement 109:1 reflecting 8:18 reflects 87:22 148:14 REGAL 2:14 regard 88:20 106:19 108:11 regarding 8:1 114:12 regardless 54:13	55:9 155:4 regimes 37:20 region 56:15 regression 101:4 101:13 regressions 145:12 regression-based 141:12 145:10,22 regression-type 151:18 regular 125:6 152:15 regularly 121:8 regulated 107:4 regulatory 165:3 rehash 6:6 reinterpret 163:11 reiterate 102:4 reiterates 102:10 relate 5:19 84:4 101:4 129:21 related 4:21 14:16 17:19 99:19 102:2 113:3 164:4,11 relates 5:22 149:9 relating 19:9 relation 82:18 100:7 103:1 relationship 83:17 111:21 121:10 relationships 100:9 relative 15:19 136:16 relatively 73:5 95:21 98:7 101:15 relax 31:20 relevant 16:1 61:6 160:18 166:20 relies 132:9 reluctant 18:20 relying 70:4 remains 4:12 remarks 4:16 5:4 94:17 158:4 171:13 remember 5:18 33:3 41:11 124:10	156:11 159:10 remind 27:12 reminded 156:8 163:16 reminds 27:19 removing 95:14 repeat 99:18 repeated 66:19 71:5 80:11 150:3 repeating 53:11 113:1 repetition 71:3 replacement 38:5 66:19 replicated 119:17 report 5:15 33:17 34:2,14 35:1 92:6 92:8,10 105:15 114:5 147:22 171:10,18 172:2 representation 61:19 120:20 represented 150:12 represents 60:18 73:12 reproductive 11:17 18:4,17 24:16 25:2 require 140:2 required 25:7 102:16 requirements 102:17 156:10,10 requires 104:17 107:6 118:14 research 10:8,9 38:1 researchers 160:11 reservoir 95:3 96:14 reservoirs 98:10 124:22 resolution 73:9 117:3 131:21 132:1 resources 161:1 respect 12:5 13:15	respond 112:11 response 17:19,20 18:3 22:9,10 97:17 133:1 162:18 responses 162:17 rest 32:6 36:16 37:19 47:7 104:20 129:8 143:19 result 17:13 22:6 82:7,8,17 167:20 resulting 42:22 results 39:11,13 40:1 47:18 54:17 55:20 56:5 57:22 92:19 118:13 166:20 167:22 resumed 85:2 return 84:21 reversibility 25:19 26:5 reversible 22:20 23:3,14 24:4,5,8 25:20 26:1,11 review 1:6 2:1 88:9 110:5 159:10 reviews 162:1,10 revisit 4:15 31:16 revisited 18:7 re-do 100:20 re-evaluating 88:11 re-review 163:3 re-sample 66:9,10 re-sampled 71:11 RICHARD 2:2,5 right 14:7 23:20 30:13 32:18 35:15 36:6 37:7,7 42:16 44:11 53:21 54:5 57:16 61:10 68:2 87:2 88:1 90:12 91:12 103:10 117:18 122:8 125:4 136:9 137:20 140:19 153:1 154:1
--	--	---	--	---

ring 105:5	R-square 154:11	43:22 46:17 48:16	schemes 40:8	seeing 54:1 81:1
ringing 139:19		49:21 50:2 52:13	SCHLENK 1:23	87:9 92:12
risk 5:19 6:21 7:10	S	52:15,19 53:3,8,9	science 2:1 84:15	seeks 88:19
9:1 25:12 30:6	safe 25:18 30:13	53:16 55:12,17	107:11 130:18	seen 4:12 16:10
88:2 123:10,13	123:20 160:6	56:22 57:11 58:9	159:5	28:2 32:18 82:5
130:17 137:5	161:9,18 162:20	60:13,15 62:5	Scientific 1:4 4:4	83:10 99:1 119:2
160:5 161:8	safety 106:22	65:10 67:2 69:7	scientifically 13:19	121:16 170:7
165:20 166:11	127:15 132:20	69:11 71:15 72:20	scope 152:4	sees 11:11
River 44:17 128:13	133:6	72:22 74:19 75:15	scratch 159:14	select 161:14
road 125:11	sample 38:3,4	76:3 78:20 79:4,8	163:4	selected 36:21 46:4
Roberson 86:10	40:19 43:2 44:7	80:7 82:13 87:7	screen 33:7 124:21	115:7
ROBERT 2:4	46:21 50:10 51:6	87:15,15 88:11,16	screening 113:18	selection 38:6,9
robust 75:15 87:3,6	51:14,20 52:7	88:18 97:2,4,7,21	scroll 46:8	140:21
165:2	53:12,17 54:16,22	100:7,10 101:17	SDWA 34:3	selectively 96:8
Rock 45:22 46:5	55:3 61:22 62:20	104:5 105:22	se 18:4	SELVAGE 2:15
48:8	64:18 65:11,15,20	106:15,16 108:12	season 36:15,16	sense 7:7 18:15
rocket 130:18	66:2 67:3 71:1	108:13 110:15,16	44:9 75:18,19,20	20:16,19 22:12
rodent 20:19 21:1	76:6 80:19,21	110:21 111:2,7	99:8	97:19 115:13
RODENTICIDE	81:9 91:1,15,21	112:17,19 113:4	seasonal 145:7	151:4
1:3	92:3,18,20 93:3	115:9 116:16	seasons 89:9	sensitive 28:1
rolling 36:20 38:20	93:10,12 94:1	118:2,13,19,21	second 10:11 14:15	161:19
38:21 55:7 59:3,6	96:15 104:13,15	120:15 121:3	16:21 36:3 83:3	sensitivity 7:7,14
66:6 77:20 79:1,3	108:15 109:8	124:20 125:9	101:1,12 102:1	170:11
90:3 93:8,18	131:22 132:3,15	126:3 127:21	103:22 127:2,4	separate 43:15
118:3,4 126:5	140:1 142:2	131:14,19 132:7	159:8	122:20
135:2 151:12	155:22 156:2	136:20 138:6	seconds 6:19	separated 28:4
152:12,21 153:7	sampled 38:18 44:8	143:11 144:20	Section 89:6	separately 98:5
room 5:7	65:7 67:21 69:3	153:12 155:3,6,6	114:10 125:20	122:22
rotated 11:11	75:9 100:8 121:8	155:10,21	137:12,21 141:10	September 8:20
rough 105:21	121:9	Sandusky 48:9	148:10	10:15 161:15
roughly 40:9 112:8	samplers 110:14	SAP 1:4,19 113:2	Sections 136:18	169:2 170:6
112:10	156:14	122:12 171:1	see 6:18 11:1 18:9	sequence 42:10
round 86:15	samples 34:9 37:2	Saturday 51:11	19:18 20:6,22	83:21
route 20:7	37:10,20 40:9,10	saw 12:11 20:16,18	21:3 46:9 51:7	serial 89:7
row 59:8	40:12 50:21,22	79:5 92:3 126:18	54:19 56:5 67:18	series 38:2 41:19
RTI 58:7 155:13	62:14 64:20 70:4	saying 55:3 112:15	73:4,6 74:18 75:4	42:19 49:3 145:17
RUBY 2:13	71:2,6,9 72:17	says 36:4 53:16	75:6,10,18,22	serious 132:21
run 53:19 68:5	73:20 75:3,4	134:10	76:18 77:1,4,7,21	serum 27:3,9
69:16 97:11	87:19 109:7 111:9	scale 49:17	78:10 79:1,7 83:3	serving 4:6
108:21 154:19	115:8,21 131:10	scared 136:3	83:6 84:18 85:16	session 1:17,21 4:9
running 66:4,9,21	131:16 136:22	scary 120:5	86:5,12,18,22	6:15 10:13,19
67:1,11 68:9	147:15 155:5	scenario 88:3	91:10 95:9 99:7	11:22 12:8 13:10
71:10	156:13 157:2	scenarios 88:2,5	110:16 123:17	14:12 20:11,15
runoff 130:1,3	sampling 3:10 9:7	127:21 153:16	125:14 134:5,5	21:22 22:14 23:6
runs 43:7 62:18	27:16 29:18 36:5	schedule 37:18	136:8 143:4	24:10 25:10 27:10
65:21 68:11,13	37:3,17,19,22	38:15	148:15 155:16	29:12 33:6 37:14
69:4,6,13	39:16 40:4,8	scheme 118:21	158:5 169:2	40:6 43:19 44:19

46:8,14,16 49:1 53:14 54:2,7,10 58:2 60:5 62:8 63:20 70:20 72:2 73:7,15 74:2 79:13 81:11 83:14 84:16 85:3 87:21 89:17 94:4,12 99:15 102:19 103:3 104:19 105:8,13 107:15 108:5 109:3,12,15 109:22 110:12 111:16 112:22 114:4,21 116:20 117:5,10 120:8 123:9 125:13,18 126:13 132:22 134:19 135:7,9 136:4,8 137:18 149:13,18 150:21 152:9 156:5 157:8 157:16 163:1 167:2 168:4,9,15 169:8 171:4 172:4	seven-day 36:14 49:15,16 50:4,7 50:21 52:12,15 55:3 78:20 116:3 134:11 seven-year 49:10 sewage 168:8 shallow 134:18 shape 89:11 114:13 137:14 140:14 143:16 144:14 149:1 shaped 145:7 shapes 87:7 139:6 144:17 sharp 99:3 143:16 sheet 45:4 Shift 109:22 shifted 152:22 short 7:16 15:19 22:7 47:10 83:1 97:3 113:15 137:9 150:5 161:3 167:4 167:5 171:8 shortcomings 159:4 shortening 151:13 shorter 40:19 75:18 77:22 79:8 98:19 102:6 111:14 116:2 137:4 138:7,9 155:9 163:18,21 shortly 167:4 short-sheets 132:20 short-term 17:7 60:20 72:10,19 77:14 113:10 115:19 116:8 146:10 166:11 show 50:6 67:17 76:16 78:7 99:3 100:9 154:7 showed 23:9 40:10 55:16 78:20 85:11 112:16 131:6 152:21 154:5	showing 49:4 55:9 75:21 95:13 105:2 105:2 shown 37:5 48:17 55:20 57:1 96:7 96:18 131:13 140:16 shows 43:8 76:22 77:16,18 97:16 side 5:6 11:14 37:5 95:3 118:16 150:18 153:4 sides 95:9 Sielken 31:2 32:16 39:18,18 40:17 43:13,13 47:6,6 49:5 52:22 53:2 53:22 54:4,9,12 58:7 61:12 62:19 63:7 155:14 sights 73:5 signaling 105:6 significance 89:2 significant 131:12 167:11,14 significantly 139:11,12 silly 55:14 simazine 76:15,17 76:19,22 77:8 similar 64:15 75:20 86:22 87:8 92:5 153:6 simple 11:5 89:21 102:9 121:4 152:14 153:2 simpler 64:8 123:7 simplest 151:17 simplify 154:15 simply 23:2 71:2,11 108:13 simulate 72:20 115:14 117:16 simulated 39:5 48:22 60:17 115:18,22 simulating 120:16	simulation 38:4,17 38:21 39:2 42:20 42:22 47:13 51:1 52:1 73:8 92:10 105:22 114:10 151:20 simulations 4:21 38:7 43:1 105:20 118:7 119:2,11 120:2 155:15 single 18:10 23:10 24:7 51:13 57:5 129:6 155:5 160:9 165:1 single-day 55:5 sit 31:20 161:17 165:8 169:5 site 27:3,8 42:9,12 49:3 75:21 76:16 77:17 sites 12:21 26:21 97:11 98:4,6 99:3 99:5 101:8,10,15 115:7 124:5,10 131:12 133:18 150:8,9,10 153:12 153:13,14,21 site-specific 45:6 100:1 sitting 157:8 165:5 six 37:20 40:10 66:8,18 80:4 136:10 162:6 166:13 six-day 50:3 size 24:7 91:15,21 92:20 93:3,12 94:1 131:5 sizes 92:3 skewed 93:22 slapped 127:12 slate 159:14 sleep 78:5 slide 32:20 33:15 34:20 35:5,5,10 35:10,12,16,18 36:3 39:14,15	40:17 46:11 47:4 48:17,18 51:16 53:4 57:1 79:5,12 slides 5:17 35:2,12 39:12 64:7 slight 152:16 slightly 47:17,20 153:3 slow 15:17 small 62:11 79:16 85:19 96:12 99:2 99:12 101:15 103:6 105:10 109:21 125:2 129:11 130:1,3 131:13 155:20 160:21 161:2 168:6 smaller 86:4,9 92:20 131:9,17 smart 170:2 smooth 119:3 141:21 142:4 154:5,13 smoothed 74:16 87:14 smoothing 142:14 142:15 153:6 soil 121:7 solely 118:1 solid 153:17,20 somebody 30:6 somewhat 93:5 103:13 104:9 143:17 soon 93:19 130:2 sophisticated 20:5 165:19 sorry 10:19 44:14 48:3 50:16 54:3 164:16 sort 7:22 26:9 28:3 51:11 71:3,13 85:13 103:14,19 103:20 104:1,4,6 104:11,14 105:21 106:4 107:3
---	--	---	--	--

108:11 112:16 140:21 142:10 145:15 153:14 155:5,7 156:2 158:9 159:11 169:6 170:9 sorts 146:1 149:2 sought 103:2 sound 148:11 sounds 11:5 89:21 source 35:21 41:16 42:19 98:15 107:3 129:2,2 sources 34:6 88:14 103:9 123:3,5 source-type 39:7 so-called 67:10 space 143:19 spaced 50:21 spacing 50:8,10 52:5 53:10,10,12 54:16,22 55:4,4 span 61:5 spatial 57:19 speak 21:21 158:7 158:10 special 159:20 speciation 7:20 specific 16:12 41:4 60:16 90:2 114:11 115:15 116:7 124:6,9 133:2 157:6 specifically 18:11 102:12 specified 59:14 speculate 169:5 spend 21:8 spent 94:14 spike 80:5,12 86:20 spikes 80:3,14,16 81:12 83:16,19,20 84:6 90:8 99:1,12 spiky 45:11,12,18 45:18,20,22 split 56:3 spontaneous 29:6	spread 52:10 67:6 square 46:5 St 44:15 48:2 staff 171:1 stage 21:19 29:4 161:9 163:11 170:11 stair-step 70:9 138:1,11,14,19 139:16 142:19 standard 91:20 108:16 143:19 standpoint 93:6 start 6:3 12:7 29:22 48:14 50:11 62:14 71:17 76:4 77:7 81:1,4 90:19 108:18 110:15 123:4 133:10 161:22 162:11 167:13 started 40:22 48:19 49:18 65:3 78:2 starting 50:14 51:3 51:4,5 52:20 60:21 61:16 66:4 72:14 120:18,19 121:1 123:3 159:14 169:7 starts 35:17 78:9,9 state 122:13 stated 129:20 132:14 134:6 151:3 statement 63:10 103:16 104:10 135:19 159:13 states 97:14,15 static 34:6 35:21 41:8 56:4 station 168:19 stationary 143:20 statistic 30:3 100:20 101:9,20 102:7 statistical 87:11 89:12 121:2	127:20 147:12 155:1 statistically 120:22 134:22 154:11,15 statisticians 94:10 110:13 statistics 94:18 124:15 127:10 147:6 step 26:8,10 48:12 64:18 65:1 66:3,8 66:18 67:5 72:15 73:21 steps 7:15 step-by-step 47:14 step-wise 65:21 Steve 45:2,19 70:21 82:3 105:18 111:11 Steven 1:17,20 2:7 stick 55:16 111:4 127:17 sticking 4:10 Stoker's 24:1 stone 27:7 stop 29:5 storage 98:9,16 story 158:11 straight 108:3 170:13 strategies 3:10 87:13 88:18 strategy 69:11 97:2 131:14 stream 95:2 96:9 96:13 103:12,18 129:15 137:15 148:20 streams 129:21 130:6,7 stream-by 103:17 Street 1:16 strength 57:19,20 120:11,16 129:2,3 strengthened 10:10 strengths 114:14 126:4 136:21	stretched 114:6 strict 142:5,9 strong 56:12 112:1 118:9 165:1 strongly 117:12 structure 143:17 144:6 structured 155:18 struggle 28:17 stuck 110:20 studies 1:7 16:15 19:15 25:3 95:13 162:3,4,14 166:22 study 19:6 107:22 132:19 160:2 163:3 stuff 23:12 29:20 subheading 105:15 submit 130:4 162:21 submitted 41:7 160:10 162:4 subsampling 116:1 subset 34:8,12 98:1 subsets 34:5 35:21 39:6 subtly 32:9 sub-daily 132:6,9 sufficient 86:7 115:13 118:15 151:14 161:6 suggest 12:4 15:21 18:20 32:21 90:6 163:3 suggested 95:7 suggesting 163:13 suggestion 14:8 suggestions 12:14 13:6 suggests 16:10 75:7 83:7 98:1 118:8 sum 115:12 summaries 162:2 summarize 162:9 167:6 summarized 17:8 39:14	summarizing 151:1 supper 19:4 supplement 99:17 supplemental 47:9 supplies 125:2 supply 48:4 support 108:9 supported 20:21 supporting 9:14 118:15 supports 107:11 suppose 81:13 90:12 supposed 48:3 sure 4:17 5:4 10:13 20:1 29:12 30:17 31:17,18 33:1 53:22 60:21 85:22 107:13 114:4 116:11 148:12 149:21 160:17,20 surface 89:5,11 128:6,15,21,22 129:4,12 surge 23:13 28:3,22 29:7 164:6 167:20 surges 28:5 surprised 85:8 surprisingly 45:12 surrogate 84:1 survives 95:20 SUSAN 2:2 suspect 98:8 99:2 sustained 18:16 80:13 Syngenta 4:20 5:3 30:22 32:1 33:16 42:6 61:3 65:16 74:12 76:10 85:14 91:11 92:4 95:7 96:4 97:11,16 100:15 105:20 110:6,9 155:14 Syngenta's 64:8 104:10 synthetic 60:12 157:9
---	--	--	--	--

system 11:12 36:11 36:17,22 39:3 41:12 44:16,18 45:8 48:4,7 75:1 75:11 86:8 96:6 96:19 99:11,13 108:19 112:5,5,15 112:19,21 118:15 119:19 120:21 121:9,16 124:14 124:16,17 143:5 144:4,16,16 145:20 152:2 168:6	91:3 96:12 99:6 103:8 109:7 123:6 152:3 159:7 160:12 162:8 168:6	ten 33:16 34:20 35:5,6,18 47:19 49:7 59:3,15 110:9	thesis 24:1	103:7,18 105:9,13
systematic 58:8 70:12,22 155:6,10 155:21	taken 34:12 92:21 103:14,21 113:11 123:1 169:12	tend 16:17 44:1 138:14,16,17	thickness 13:7	106:5,9 108:6,10
systematically 50:11	talk 8:4 14:14,18 26:13 32:19 86:10 107:3 121:19 122:7 128:7 158:19,20 169:6 171:9	tended 135:12	thing 10:22 12:22 13:2,5 26:17 29:1 61:14 69:11 75:17 92:11 97:17 113:17 117:19 119:1 127:19 149:19 153:10 156:17 159:12 160:4 163:16 166:17 170:10	108:12,21 109:1 110:6 112:13 113:1,12 114:2,6 115:11 116:4,9,18 116:21 117:6,19 117:20 120:1,2,6 122:5 124:2,10,12 125:14,16 127:1 127:13,16 131:5 132:20 133:9,11 133:15 135:21 138:11 141:2 142:6 144:2 145:20 147:8,19 148:6,10,18 149:10,15 150:6 150:16,19 151:17 152:7 154:20 155:1,13,21 157:4 157:14,22 159:1,3 159:4 160:14 163:5 164:19,22 165:3,9,10,12,18 165:21 166:6,14 167:2,7,18 168:2 169:11 171:19
systems 9:20,21,22 10:6 34:9 36:12 44:13,15 45:5 70:2 76:1 86:4,9 86:12,19,21 87:9 96:12 98:3,10,13 106:13 109:6,20 109:21 112:10 114:18 118:12 121:20,22 131:15 131:16 144:10 151:6,10 152:4	takes 146:22 152:6	tendency 92:14 133:2	things 13:16 15:21 22:2,11 23:21 27:5 70:5 80:18 86:2,3 91:14 98:20 100:13 110:13 111:15 119:7 128:4 135:4 151:1 152:11 157:17 159:2,22 167:6,14 168:17 170:3	170:3
	talking 7:5 10:21 23:1 33:22 35:4 46:10 70:17 76:8 87:5 94:20 98:21 98:22 103:7 107:9 110:6 111:12,17 121:17 125:5 127:3,19 159:10 162:6 165:7	term 77:15 79:8 113:15 116:2 138:8 139:14 163:21 166:12	think 6:10 11:3 12:10,17 13:8,16 13:18 14:6 16:17 16:21 17:9 18:11 20:3,13,15 21:6 21:10,21 22:17 23:4 24:1,11 26:4 26:15,19 27:6,6 27:20 28:11,15 29:21 30:19,22 31:1,16 32:5 33:19 34:16 35:11 40:6 46:5,10,12 64:8,11 68:4,10 69:4,6,19 70:4,9 71:16,21,22 72:4 72:6 73:15,18,21 73:22 77:2 78:21 79:10 84:2,14 86:1,9 87:3,9,18 90:13 91:6,11 92:5 93:1,2,10 94:2,6 95:21 96:4 96:11 98:21 102:4	166:17 170:10
	talked 6:6,18,20 7:3 11:5 14:13 15:12 32:8 99:22 115:1,4 152:12 166:18 170:8	terms 7:1 14:7 15:4 15:10 18:19 27:3 74:9 78:15 82:13 83:11 87:17 129:1 134:4,6,15 138:13 153:8 154:16 155:9 160:22	thinking 15:1 19:2 29:17,22 105:19 111:13 152:18 153:10 157:9 165:13,17,19 166:2,7,9 167:21 170:17	166:17 170:10
	talks 146:22 152:6	test 55:11 56:19 77:6 113:18 116:1 155:18	third 57:6 79:19,21 79:22	166:17 170:10
	talks 146:22 152:6	tested 37:4 62:6	thought 27:13 79:14 85:19 92:7 93:16 98:20 114:3 124:2 132:2 135:13,13 150:22 152:11	166:17 170:10
	target 12:20 26:21 27:3,8 52:5,15 55:5,6,7,10 57:5 60:4 64:4	testing 49:22 127:6	thoughts 6:7	166:17 170:10
	tangent 156:7	Texas 56:14	thousand 43:1,7 66:21	166:17 170:10
	tap 81:14,15,17	thank 4:10 10:10 30:19 32:2 33:3 33:11,12 40:14 46:7 47:7 53:1 62:7 63:19,20 64:6 94:4,6 99:14 99:15 104:19 132:21 149:13 150:20 169:8 170:4,21,22 171:4 171:15,19,20 172:1,4	three 5:2 7:5 11:1	166:17 170:10
	target 12:20 26:21 27:3,8 52:5,15 55:5,6,7,10 57:5 60:4 64:4	thanks 171:2		166:17 170:10
	task 161:3 163:12	theme 146:19		166:17 170:10
	team 158:8 170:5 170:15 171:2	theorem 93:21		166:17 170:10
	technically 156:4	theorems 139:20		166:17 170:10
	tell 41:5 59:16 111:17 161:21 170:19	theory 93:17 147:5 147:5		166:17 170:10
	temporal 14:16 15:2,3 16:8 29:8 57:19 89:4 112:6			166:17 170:10
	temporally 102:21 103:1			166:17 170:10
				166:17 170:10

25:5 37:9 44:15 45:13 54:21 62:16 62:22 63:5 65:14 66:5 71:18,18,18 71:20 81:17 97:16 107:9 136:14 148:7 154:12 164:3 three-day 50:3 53:9 55:6 66:4,6,9 66:21 67:1,1,3,11 67:21 68:9 69:2,8 156:20 three-node 140:17 threshold 26:9 81:7 81:8 105:1 133:7 134:7 throw 79:12 123:4 Thurman 31:3 63:21 74:4,5 80:17 82:15 85:3 85:22 88:8 106:8 107:16 114:9 122:9,10 125:16 125:20 127:8 136:2,6,10 147:21 148:3 152:20 157:15 Thursday 1:12 51:4 ties 145:10 tight 133:20 time 15:4,7,11 16:22 17:3 19:4 20:4,22 21:3,7,11 22:16 30:2 34:5 37:14 41:19 42:19 49:3 55:8 58:10 61:5 63:17 73:3 82:12 84:20 86:16 90:12,17,20 93:7 98:18,19 102:15 108:20,22 109:8 110:20 111:3 112:18 118:19 137:3 143:14 145:17 151:8	152:3,5 156:15,18 158:17 161:3 162:15 163:17 168:20 timers 169:17 times 20:1 25:22 32:18 66:19 70:22 72:17 82:12 83:9 102:5 105:14 109:20 117:21 118:21 131:21 timescale 73:13 118:10 time-based 16:19 time-weighted 156:19 timing 77:5 130:9 today 34:15 166:19 167:10 172:3 told 94:15 tons 60:12 Tony 27:19 tool 26:20 tools 113:21 top 11:2,6,6,13 12:3 48:17 topic 157:20 topics 158:1 169:14 tornadoes 6:16 total 76:9,13,21 84:2 145:15 totally 25:19 33:14 68:22 touch 94:18 touched 12:18 tough 45:20 tox 16:14 77:13 toxicity 7:18,19 10:16 12:18 14:17 15:3 88:22 132:13 132:19 toxicological 5:22 17:3 88:9 156:10 toxicology 23:5 28:16 31:19 150:18 track 156:4 168:17	168:22 tracks 29:5 161:2 train 161:2 168:17 169:3 trained 95:18 trains 168:18,20 transition 29:18 translate 83:19 156:9 translated 123:18 translating 30:11 transport 129:14 130:15 transported 129:17 transposed 11:9 treat 86:11 treated 98:5 115:8 treatment 62:13,17 86:12 95:14,17,18 95:19,20 122:11 122:13,20 treatments 58:14 123:4 tremendous 60:11 trend 155:22 trends 155:8 Triangle 38:1 triangles 75:3 76:18,20 triazines 113:19 trickery 47:13 trickle 12:7 trigger 26:10 113:21 tri-weekly 50:4 true 37:1 39:2 41:22 44:15 52:7 53:20 60:22 62:21 64:21,22 65:6,7 67:10,12 68:12,13 69:5,7,13,14 119:4 128:3 151:21 truth 60:17,18 61:5 61:13 72:11,14,16 73:2,12,13 75:13 75:14 76:4 87:6	102:8 106:1 115:9 115:18,22 138:12 148:12 try 14:20 21:6 22:2 22:11 63:18 65:13 75:13 76:16 86:11 86:16 87:16 108:22 119:11 133:3,4 trying 20:14 21:8,8 21:9 27:12 29:17 33:3 52:5 63:11 70:16 73:3 77:13 108:21 123:6 133:10 138:13 149:3 150:16 165:8 168:19 Tuesday 38:13 51:4 Tuesdays 51:9 tumor 12:6 167:19 tuning 146:14 turn 4:7 47:3 111:3 113:14 158:4,20 169:19 171:11 turned 62:5 74:22 turns 23:17 twelve 59:19,20 60:4 twice 132:3 twist 61:5 two 6:9 22:11 36:15 37:9,10,10 43:15 43:17 44:16 46:3 50:2 57:9,12,16 58:6 64:14 65:1 66:5 68:6,18 71:18 81:16 83:7 94:9,10 99:3 100:6 103:6,12 105:4 107:21 114:10 115:16 118:4,5 129:1 136:12 137:21 139:7 143:15 148:7 154:7 157:10,17 158:13	159:22 164:3 168:18,20 169:21 two-day 53:9 113:16 156:19 two-liter 81:15,22 two-weekly 37:18 type 35:21 40:1 73:2 75:5 77:19 95:16,17 101:2,11 104:7 113:16 156:21 types 128:9 typical 45:4 106:6 119:13 typically 82:6 <hr/> U <hr/> ultimately 156:9 unacceptably 91:20 unaffected 95:21 uncertainties 107:22 123:19 uncertainty 84:19 88:20 89:10 106:4 106:5,6,9,17,21 106:22 126:2 127:5 161:8 unclear 17:12 underestimate 44:1 44:10 70:11 underestimated 67:13 70:8 underestimating 44:4 68:1 underestimation 138:5 139:17 underlies 47:4 underlying 47:3 73:1,8 underneath 48:18 understand 5:2 11:16 22:15 29:19 29:20 31:17 32:12 33:20 62:12 63:12 64:17 73:16 80:6 127:1
---	--	--	---	--

understanding 24:20 26:4 63:16 84:19 96:1 118:11	value 29:10 30:10 37:1 41:22 45:10 52:6,6 60:4 71:10 81:7,8 93:17 100:10 106:11 107:8 133:8 134:11,11 138:3,5 138:6 140:1,3,16 141:15 144:18,19 147:4 156:19,20	Vecchia 145:3 verging 79:21 80:11 version 11:12 33:10,14 versions 119:3 versus 14:17 15:2 18:9 22:8 viability 23:21 view 79:18 81:19 88:6 117:12 134:4 157:7 views 171:22 vision 64:3 vitro 1:7 13:9 VMP/AMP 34:4,12 57:20 volumes 162:5,6 vulnerable 21:19 98:2 151:6	wanted 13:11 20:12 29:16 45:14 47:14 58:20 61:22 68:14 68:16 76:15 77:13 78:7,17 81:11 87:16 98:12 107:13 112:21 127:17 128:19 149:15 160:17,20 163:6 wants 117:22 118:2 warned 6:2 136:4 warning 6:13 WARP 97:9 101:2 119:12 121:5 129:6 145:5 151:5 Washington 1:17 12:12 wasn't 22:20 48:3 60:1 70:8 163:2 164:20 wasting 37:15 watch 116:6 water 1:7 3:9 5:21 9:7 15:14,18 21:11 33:22 34:6 34:8 35:18,21,22 36:10,10,12,17,22 39:3 41:12 44:17 44:18,20,21 45:5 45:7 48:4 55:17 57:11,13 59:18 61:18 63:12,13 74:14,15,17,19 75:2,4,5,6,8,10 76:1 80:7,8 81:14 81:15,16,17 84:10 85:11,14,18 86:4 87:4,9,19,20 88:14,14 89:3 95:3,9,12,16 96:6 96:8,12,15,19 98:3,10,13,15 99:8 106:13 107:20 108:19 109:6 113:20 120:21 121:8,15	121:15,16 122:11 122:13,18,19 123:4,11,13 124:22,22 125:2 125:11 128:6,15 128:20,22 129:1,4 129:12,14,15,19 130:9 131:1,15 132:15 137:8 143:5 144:4,10 145:19 150:10 151:6 157:10 160:4 168:6,7 waters 89:6,12 123:17 watershed 146:17 waved 156:16 way 11:1,2,9 13:6 14:9 24:12 45:11 50:6 53:10 63:15 64:3 66:5 71:19 72:11 80:7 86:2,3 91:1 101:6,19 103:1 104:2 107:16 120:3 134:8 151:15 155:18 165:16,19 166:9 168:3 ways 32:10 133:12 145:1 159:7 160:7 weakness 120:18 weaknesses 114:15 126:4 136:21 weapons 27:19 weather 128:10 137:15 148:20 weather-related 83:10 Wednesday 51:4 weed 128:16,17 weeds 74:7 week 38:9,9 44:8 78:22 139:15 weekly 37:12,17 48:15 50:4 74:19 79:4 87:14 106:12 weeks 28:9 36:15
unique 71:1,14 unmonitored 101:10 update 122:15 upper 126:6 uptake 15:13 up-peak 80:13 use 19:7,16 21:3,5 26:19 29:7 40:7 48:12 50:7 52:15 61:11 76:15 81:2 91:13 93:22 95:4 95:8,22 100:1 104:13 111:6 112:1 113:17 121:10 124:3,16 125:22 128:18 129:9 137:16 140:2 144:13 148:21 150:14 151:5,19 168:3 useful 141:9 146:10 147:17 uses 77:4 96:20 121:13,13 142:7 usual 111:14 usually 132:16 157:17 utilization 13:14 U.S 1:1 95:4 96:7 97:14	values 43:4,9 50:15 50:16,17 53:7 59:15 61:19 62:6 63:13 65:17 67:8 69:13 71:14 79:2 91:8 92:12 95:5,9 95:22 118:4 137:22 138:4 139:18,19 142:11 143:11 146:15 147:13 variability 49:13 51:8 56:13,18 63:12,16 73:10 88:21 97:12 103:9 103:14,20 108:1 112:16 119:6,14 119:18 120:2 123:3,5 127:14,20 129:7,8 130:8 132:8 148:14 151:21 variable 49:6 75:9 95:15 135:18 144:8 variables 112:3 variance 93:11,14 155:11 156:1 variants 157:1 variation 128:8 varied 54:15 variety 128:10 various 9:15,17 130:10 136:17 149:22 vary 89:15 102:3 varying 126:3	wait 29:6 want 6:5,7 8:11 10:14 14:3,9,14 19:11,22 25:8 30:17 31:16 55:14 58:5 60:7,14 62:8 68:4 69:14,16 74:1,4,5,7,10 79:10 83:15 87:2 90:2,3,4,5,8,9,13 90:16 91:16,18,21 100:3 102:4 103:5 103:15,22 104:9 107:19 109:15 112:14 117:21 120:7 122:10 123:16 127:13 131:19 132:1 134:21 135:4 142:17 144:3 145:19 146:20 147:2 150:2 157:3 159:7 167:3,6 169:5 170:4 171:6 171:11,14,20	W wait 29:6 want 6:5,7 8:11 10:14 14:3,9,14 19:11,22 25:8 30:17 31:16 55:14 58:5 60:7,14 62:8 68:4 69:14,16 74:1,4,5,7,10 79:10 83:15 87:2 90:2,3,4,5,8,9,13 90:16 91:16,18,21 100:3 102:4 103:5 103:15,22 104:9 107:19 109:15 112:14 117:21 120:7 122:10 123:16 127:13 131:19 132:1 134:21 135:4 142:17 144:3 145:19 146:20 147:2 150:2 157:3 159:7 167:3,6 169:5 170:4 171:6 171:11,14,20	valid 62:13,17 96:5 valleys 153:8 valuable 87:3,10,11

37:9,12 38:15 78:21 109:13,17 110:1 130:4 169:21 171:18 weight 8:22 9:14 13:4 weighted 34:13 152:17 153:5 156:19 weights 9:16 153:4 153:4 well-characterized 114:1 well-known 113:22 Wenlin 42:5 44:14 45:14 went 23:17 24:2 31:14 37:18 49:14 49:19 68:1,6 85:1 165:6 weren't 75:9 White 41:7 97:14 140:18 142:8 146:5 147:4 154:3 Whitmore 33:18 wholesale 87:2 wide 49:15,15 110:18 widely 52:10 wider 153:3 WILLIAM 2:6 WILLIAMS 2:16 window 38:5,5 42:21 49:15,15,16 78:15 110:20,21 153:3 156:2 windows 33:13 38:2 46:18,22 58:10 110:18 155:12 wise 48:13 wish 157:21 wishing 163:2 woman 29:4 132:14 women 30:1 wondering 80:15 168:18	word 23:20 33:9,10 words 13:18 90:18 108:18 124:9 134:9 work 11:19 28:10 38:1 39:8 73:4 75:16 80:15 93:1 93:2 112:3 121:22 129:5 132:12 139:16 145:6,11 147:1,10,15 149:9 151:11 169:18 171:15 worked 39:5 51:19 57:18 154:6 working 5:1 8:15 78:2 107:17 171:17 works 37:9 153:20 world 11:17,19 14:4 79:15,19 160:11 worried 13:21 worries 141:16 worry 100:22 worst 44:21 52:11 57:12,16 71:21 worst-case 88:2,3 153:16 worth 49:2 94:3 113:12 151:8 worthy 20:2 wouldn't 14:3 65:4 119:19 142:17 wrap 3:22 62:9 63:9 wrestled 106:8 write 5:15 30:18 write-ups 150:1 writing 87:19 written 126:10 wrong 63:22 127:3 165:11	42:9,11,20 48:2 56:13,13,16,18,18 58:9,18 72:18 75:2 86:15 89:9,9 90:17 98:15 110:8 113:2 115:21 125:9 128:2,2,5,5 128:7,7 139:1 145:16 158:13 yearly 48:5 145:15 years 13:13 36:11 36:17 39:3 45:7 49:2,6,7,8,9 90:21 108:12 122:12 144:10 158:11,14 year's 111:17 year-specific 45:6 yesterday 6:6,9 8:5 12:18 15:12 17:10 19:3 20:15 47:11 159:1,9 160:20 166:19 young 2:17 25:13 35:3,3,8,13,15 39:11 40:3 42:2 42:14,17 89:17,18 108:7,9 117:10,11 135:7,8 147:8 150:21,22	1.1 44:3 1.24 106:2 1.5 106:2 1.9 3:7 4:16 5:18 6:17 85:5 10X 107:7,7,8 10-day 60:2 10:17 84:17 10:18 85:1 10:35 84:21 10:38 85:2 1001 1:16 101 128:21 159:12 114 3:15 12 36:3 39:14 12.5 106:11,18 12:14 172:6 120 98:6 125 3:17 13 47:5 49:2,8 68:5 68:17 69:7,12 13-year 49:9,10 130 46:5 136 3:19 137 36:12 14 29:6 40:17 14th 1:16 15 84:17 15-minute 27:14,18 165:1 167:10 169 3:22 17 37:20 18 52:8 1993 23:8	166:3 200 105:4 2001 41:6 2003 137:5 160:1 163:18 2004 100:13 115:6 2008 145:4 2009 40:4 2010 1:13 8:20,21 202 48:1 51:18,19 51:21,22 53:7 56:3,11 59:17 61:15 21 54:8 22 53:18,20 54:1 25 40:9 52:12,16 54:6 131:3 26 40:9 139:15 27 98:2 28 28:9 53:16 54:17 28-day 28:7 53:10 29 1:13
				3
				3 17:8 3X 106:18 3.6 28:9 30 6:19 31:5 59:3 62:18,22 63:5 64:19 65:17 68:15 69:14 72:17 73:20 110:18 115:21 165:1 166:12 30-day 60:3 31 34:10 52:9 31.5 68:2 35 46:5 64:19 65:18 72:17 351 49:8,8 363 66:6 71:19 365 36:19 64:20 65:20 66:6 71:1 71:19,20,22 73:19 365-day 38:19 41:19 42:19 43:3 37.5 106:11,15
				4
		Z		
		zero 62:22,22 68:15 zoom 33:10,11		
		0		
		0.25 131:3 0.75 52:7,8,11 0.7548 54:6 0.79 54:7 0.80 52:9 0.95 91:18 0.96 51:9 0.97 51:9 0.99 91:22		
		1		
		1 34:9 1,000 38:7		
			2	
			2 3:8 2.1 3:13 88:7 2.2 3:15 114:8 2.3 3:17 125:19 126:20 2.4 3:19 136:3 2.6 44:3 20 44:1,2,10 55:5 63:4,5,5 81:2,14 91:19 110:18 134:11 159:6,7	

4 3:3,5 40 31:5 57:8,14 115:21 441 36:10,17 45-minute 27:19 4500 66:19 70:22 48,000 34:4 <hr/> 5 <hr/> 5 3:7 5.2 89:6 5.4.1 136:18 137:21 141:10 5.4.2 125:21 5.5 114:11 5.5.3 137:14 5.6 136:18 140:5 5.7.1 137:12 148:10 5:00 29:1 50 134:12 162:11 50th 54:3,4 67:7 50,000 34:3 <hr/> 6 <hr/> 6.2 28:9 60 57:8 166:12 65 57:7 <hr/> 7 <hr/> 7 138:21 70s 20:3 <hr/> 8 <hr/> 8:30 1:15 8:34 4:2 80 44:2,10 88 3:13 <hr/> 9 <hr/> 90 54:20 59:3 65:17 71:1 72:1 78:10 97:15 139:14 172:3 90th 42:12 90-day 36:5,20 38:20,21 39:2,15 39:16 55:7 60:3 71:22 78:2,12	151:12 91 71:13 92 71:14 94 97:13 95 127:11,12 95th 41:21 43:3,9 54:18,20 96 97:15 97.5 54:20 99 69:18 99th 41:21 42:13 43:4 59:16 60:1 90:11 99.99 90:10			
---	--	--	--	--